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Long-Run Price Elasticities and Mechanisms: Empirical Evidence from Residential Electricity Consumers

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Long-run price elasticities and mechanisms:

Empirical evidence from residential electricity consumers

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Long-run elasticities, while difficult to empirically estimate, are critical inputs for welfare analysis, demand forecasting, and policy evaluation. In this paper, I leverage a novel source of exogenous and persistent price variation to estimate the long-run price elasticity of demand for residential electricity consumers. I find that consumers are much more responsive to prices in the long run than the short run, with a long-run elasticity estimate of -2.4, in contrast with a short-run elasticity estimate of -0.36. Low-income consumers are particularly responsive to prices in the long run, emphasizing the importance of bill salience to low-income households. I explore some of the mechanisms driving this price response, and find that households facing higher prices are less responsive to temperature than those facing low prices. My findings highlight the importance of getting electricity prices right, and suggest that retail electricity prices might play a more significant role than previously thought in determining the pace of energy transitions to cleaner technologies.

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1 Introduction

Long-run price elasticities of demand are among the most important parameters in the field of economics. To conduct welfare analysis, forecast future demand, and evaluate policy impacts, long-run elasticities are vital components. This importance notwithstanding, there are few experimental or quasi-experimental empirical estimates of long-run price elasticities.

The dearth of experimental and quasi-experimental long-run elasticity estimates is a product of challenging empirical conditions – to empirically estimate a long-run price elasticity, one must leverage a long-lasting source of price variation that gives consumers time to adjust their behaviors and investments and reach a new equilibrium. Sources of persistent exogenous price variation are rare, however, and many estimates therefore rely heavily on structural modeling and assumptions surrounding the underlying utility function. (Kamerschen and Porter, 2004; Dergiades and Tsoulfidis, 2008; Alberini and Filippini, 2011).

In the field of energy, long-run price elasticities of demand are critical for several reasons. First, long-run demand forecasts are used by grid planners and utilities to make long-term planning and infrastructure investment decisions. Second, numerous energy policies impact retail electricity prices either directly or indirectly. [1] Evaluating the potential impacts of these policies depends on understanding how consumers will respond to retail prices in the long run. Finally, the speed and scale of clean energy transitions and the policies to accomplish such a transition will depend in part on how consumers respond to prices in the long run.

In this paper, I leverage a novel source of persistent spatial price variation to estimate short- and long-run price elasticities for residential electricity customers in California. This price vari-

[1]Policies that directly impact retail electricity prices include rate reductions for low-income households, special rates for adopters of technology like rooftop solar or electric vehicles, and carbon taxes. Other energy policies and technologies have been shown to indirectly impact electricity prices, including electricity market deregulation(Borenstein and Bushnell, 2015), plant closures(Davis and Hausman, 2016), and renewable energy generation(Kyritsis, Andersson and Serletis, 2017).

ation is driven by a subtle feature of California's pricing regime. In the increasing block pricing rate structure used throughout California, marginal prices increase when electricity usage exceeds a certain threshold. Because of differences in heating and cooling needs for households across the different climates of California, utilities set these thresholds to different levels depending on where a consumer lives. Within Pacific Gas & Electric's (PGE's) service territory, there are ten different baseline territories[2], with the boundaries for these territories often determined according to discontinuities in a household's elevation. These boundaries have led to long-lasting persistent price variation since they were established in 1982, with one side of the border consistently facing higher prices than the other. I leverage these price discontinuities to estimate elasticities across different time intervals.

Estimating a long-run elasticity that spans more than a few years is empirically challenging, as the panel methods commonly used in the literature can miss important margins of response. Standard panel methods compare consumption before and after a price change, relying on counterfactual data on a consumer both before and after the change in price. Notably, they miss cross-sectional consumption differences created when homes are built or when new tenants move in (often a time in which home renovations occur) under different price regimes across space.

The persistence in cross-sectional price variation in the setting of this paper provides excellent an empirical setting to estimate long-run price responses. I leverage this cross-sectional price variation driven by the levels of the baselines across baseline territory boundaries to estimate a long-run price elasticity of demand. By leveraging this cross-sectional variation, I capture a more comprehensive measure of demand response. I estimate a long-run elasticity of -2.4.

To anchor this result within the existing literature, I use standard methods to estimate a short-run price elasticity of demand. In the short run, I follow the methods of Ito (2014), using a

[2]These baseline territories were finalized in 1982 and have largely stayed the same since 1982 (PG&E, 2020).

simulated instrument to isolate exogenous variation in the price schedule over time. I find that electricity consumption is relatively inelastic, with an elasticity of -0.36 in my preferred specification, indicating that consumers are much more responsive to permanent price changes in the long run than to short-run price fluctuations.

To better understand the estimated difference between short-run and long-run elasticities, I explore possible mechanisms that would drive such large price responses in the long run. Notably, I do not find that consumers are responsive to long-run prices in their adoption of rooftop solar or utility energy efficiency programs[3]. However, consumers facing high prices are significantly less responsive to changes in temperature than those facing low prices. This effect is magnified the longer a customer has lived in a single location, particularly during summer months during hot temperatures . While I don't directly observe adoption of air conditioning, these results are consistent with households responding to electricity prices in their air conditioning adoption choices.

Furthermore, substantial heterogeneity exists in price responsiveness according to a consumer's income level. There are several explanations that might explain this conflict – electricity bills may be more salient to low-income households as they have less discretionary income than higher income households. However, higher income households likely have more appliances, leading to more margins for response to price changes. Furthermore, durable goods that reduce consumption often have high capital costs, leading to potentially greater adoption among higher income households (Borenstein, 2017). I estimate elasticities for households with different income levels, finding that low-income consumers are less responsive to changes in prices in the short run, but that in the long-run, this trend reverses and low income consumers are actually more responsive than higher-income consumers.

The long-run elasticity and mechanisms estimated here are specific to the geography and climate

[3]In this paper, I observe the adoption of energy efficient appliances when a consumer enrolls in a utility energy efficiency program. This is only a portion of energy efficient appliance sales, and the energy efficiency adoption estimates presented here can be thought of as lower bounds.

in this northern and central California sample, and there are reasons to expect a relatively high long-run elasticity in this setting. Electricity prices are particularly high in California, leading consumers to be more aware of their electricity bills. Air conditioning adoption is lower in California than in most states in the United States, leading to more opportunity for new AC adopters. And rooftop solar adoption and potential are also higher in California than many other settings in the United States, creating better conditions for that margin of response. However, one should expect elasticities to be much larger in the long run than the short run across all geographies, as consumers have more time to make adjustments to their behaviors, adopt durable goods, and choose housing characteristics that impact electricity consumption in the long run.

This paper contributes to four distinct literatures. First, this paper contributes to the literature estimating long-run responses to energy prices. Within the field of energy economics, most papers estimating long-run elasticities use aggregated data and structured dynamic panel models. These papers, including Alberini and Filippini (2011), Kamerschen and Porter (2004), and Dergiades and Tsoulfidis (2008) rely on strong assumptions about the form of serial correlation and typically estimate long-run elasticities in the range of -0.3 to -1.1. There are few papers that use quasi-experimental methods to estimate long-run elasticities, most notably by Deryugina, MacKay and Reif (2019) and Feehan (2018). Deryugina et al. estimates price elasticities spanning a time horizon of up to three years[4], finding a price elasticity of -0.09 in the first six months and -0.28 after 30 months. Feehan (2018) is perhaps more closely related to this work, where the author leverages a natural experiment in Canada to estimate 20-year elasticities for residential electricity customers, finding a long-run elasticity of -1.2. This paper builds on the conclusions of these studies by directly estimating mechanisms of response and by exploring heterogeneity in both the short and long run.

Second, this paper contributes to the literature on durable goods investment, especially in re-

[4]The authors forecast a long-run elasticity spanning up to ten years, but are unable to test this estimate with quasi-experimental data.

sponse to input prices. Here, I estimate how adoption of solar and energy efficiency measures varies in response to electricity prices. Work by Chesser et al. (2018) and Crago and Chernyakhovskiy (2017) explore the impact of electricity prices on investment in rooftop solar, using aggregated data to show that electricity prices are an important drivers of residential solar adoption, with higher electricity prices leading to greater solar adoption. Davis (2020) shows that electricity prices are an important determinant of choice of heating type and electrification. Bushnell, Muehlegger and Rapson (2021) finds that electric vehicle adoption is impacted by electricity prices, though gasoline prices are more impactful. This paper builds on that work by using administrative customer-level data to estimate how individual customers respond to within-utility price differences. Furthermore, this paper is the first to directly attribute long-run price responsiveness to durable goods mechanisms.

Third, there is a large literature that estimates short- and medium-run elasticities for residential electricity customers. This paper builds primarily on works by Ito (2014), Shaffer (2020), and Brolinson (2019) that estimate short-run elasticities with respect to both marginal and average prices in settings with increasing block pricing. I build on this literature in two ways: first, I leverage a novel source of within-utility cross-sectional price variation, which improves on the current literature by reducing the potential for confounding non-price effects[5]. Additionally, I expand on existing methods to estimate dynamics in the medium-run, showing that consumers continue to respond to prices lagged up to four years but that responsiveness diminishes over time. There are numerous other papers that estimate short-run elasticities for residential electricity customers. A 2018 meta-analysis (Zhu et al., 2018) of papers estimating price elasticities of demand for residential electricity customers estimates a mean short-run elasticity of -0.23. In this setting, I estimate a short-run elasticity of -0.18 with respect to marginal price and -0.36 with respect to

[5]Brolinson (2019) leverages a similar source of source of cross-sectional variation, but is limited by data on a much sparser set of households. Here, I use a rich set of households, allowing me to directly compare households on either side of the the border in order to credibly estimate elasticities.

average price, grounding this analysis squarely within the existing literature.

Finally, this paper contributes to the literature exploring how household income impacts price responsiveness among residential electricity customers. Evidence in this literature is somewhat conflicting – Alberini, Gans and Velez-Lopez (2011) and Reiss and White (2005) find that price elasticities of demand are highest among the poorest households and monotonically decrease as income grows, while Brolinson (2019) and Schulte and Heindl (2017) find that wealthier households are more responsive to prices. Recent work by Cong et al. (2022) finds that low-income households wait until higher summers temperatures to turn on their air conditioning. This paper is the first to separately quasi-experimentally estimate short- and long-run price elasticities by income. I show that while higher income households are much more responsive to prices in the short- and medium-run, this trend reverses in the long run. This suggests that bill salience is particularly relevant among low-income households and that investment in durable goods may play a significant role, even among a low-income population which may have capital constraints.

The paper proceeds as follows: Section 2 discusses background on the setting and measures of heterogeneity used; Section 3 presents the data and empirical strategy; Section 4 presents estimates of short-, medium-, and long-run price elasticities; Section 5 explores the mechanisms driving these responses to price; and Section 6 concludes.

2 Background

2.1 Increasing block pricing and baseline territories

The setting for this paper is Pacific Gas & Electric (PG&E), a large investor owned utility company in Northern California. PG&E uses a non-linear price schedule called increasing block pricing to set prices for electricity. This pricing mechanism is similar to a graduated income tax, where higher

levels of usage face a higher marginal price. As an illustrative example, suppose Customer A uses 1000 kWh in a month. In one region of PG&E's service territory (Baseline Territory Q), she would pay 18 cents per kWh for the first 888 kWh (Tier 1) she uses and 24 cents per kWh for the next 112 kWh (Tier 2) she uses, leading to a total bill of $186.72. In this two-tier example, 888 kWh is the monthly *baseline allowance* – after reaching the baseline, all further consumption is in the second tier and faces the higher marginal price.

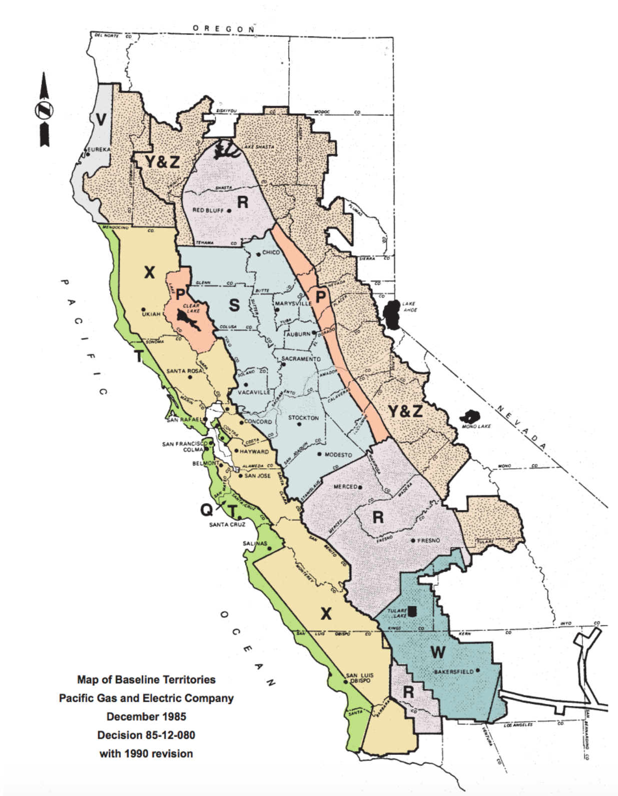
There is a great deal of variation in climate even within utility service territories. PG&E's service territory includes both Fresno, with an average June high temperature of 92 degrees, and San Francisco, with average June high temperatures of 60 degrees. Because of this wide gap, electricity demand to meet basic heating and cooling needs across a utility's service territory is not equal. As such, customers are divided into climate territories that determine the baseline – in other words, the level of electricity that can be used before the higher marginal price takes effect. Furthermore, baselines are different in summer and winter, as well as for customers with electric versus gas heat. Continuing with our illustrative example, suppose that Customer B has identical usage, but lives in a territory (Baseline Territory T) where the baseline allowance is 447 kWh per month. She pays the same price, 18 cents per kWh, for the first 447 kWh, but then pays 24 cents for the next 553 kWh, leading to a total bill of $213.18 – about $26 higher than Customer A for the exact same level usage.

PG&E divides its service area into ten different baseline territories[6], as shown in Figure 1. These baseline territories were established in 1982[7] by the California legislature, and adopted by by the California Public Utility Commission in 1983. Between 1983 and 1990, the CPUC continued to make small changes to where the baseline territory boundaries lay. From 1990 to 2019, the

[6]Note that PG&E's baseline territories are different boundaries than the California Electricity Commission's (CEC's) "climate zones," which are used to determine building codes. Baseline territory boundaries are nearly universally separate from CEC climate zone boundaries, with a very small number of exceptions.

[7]A precursor to baseline territories was established in 1976, called "climate bands," though there were only four climate bands based purely on heating degree-days.

Figure 1: PGE baseline territories (PGE, 2020)

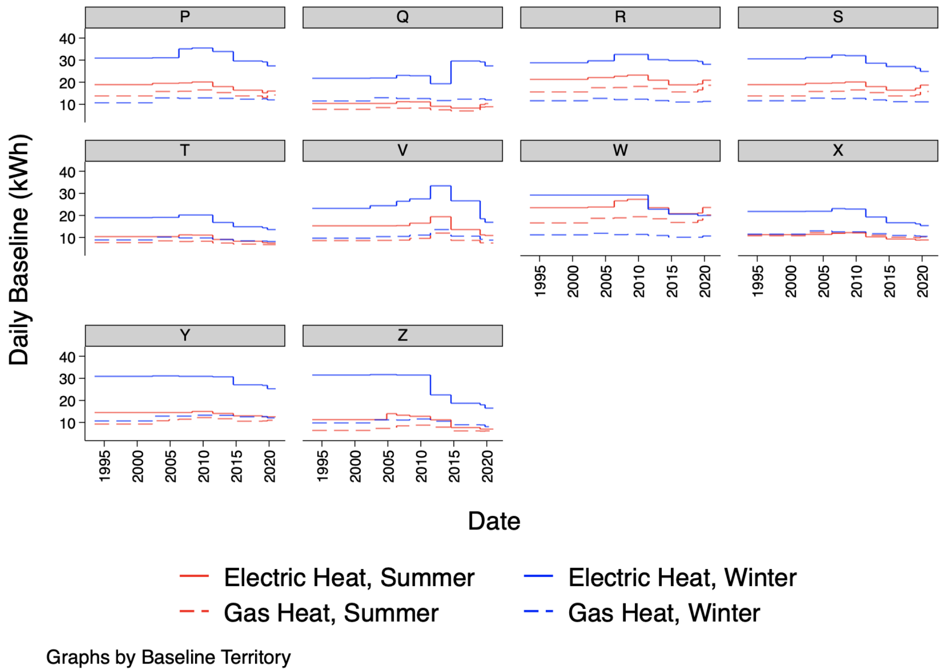


Note: This map shows PG&E's baseline territories. These borders did not change from 1990 to 2019. Source: PG&E

baseline territory map stayed the same, with an adjustment to one community in 2019. This community has been dropped from the sample, meaning that the baseline territory boundaries are constant over the sample period of this study. More generally, baselines are determined based on two potential factors: geopolitical demarcations (e.g. zip code/city/county boundaries, roads) and elevation discontinuities. For example, Santa Barbara County is divided into Territories R, T, and X according to geopolitical demarcations. However, Trinity Country is divided into Territories X, Y, and Z, where residents of Trinity County below 2,000 feet of altitude are in Territory X, residents between 2,001 feet and 4,500 feet are in Territory Y, and residents above 4,500 feet are in Territory Z. A full list of baseline territory boundaries defined by elevation is provided in Appendix A.3[8].

[8]A full list of baseline territory definitions including those defined by non-elevation definitions can be found at https://www.pge.com/tariffs/assets/pdf/tariffbook/ELEC_PRELIM_A.pdf.

Figure 2: Baselines over time



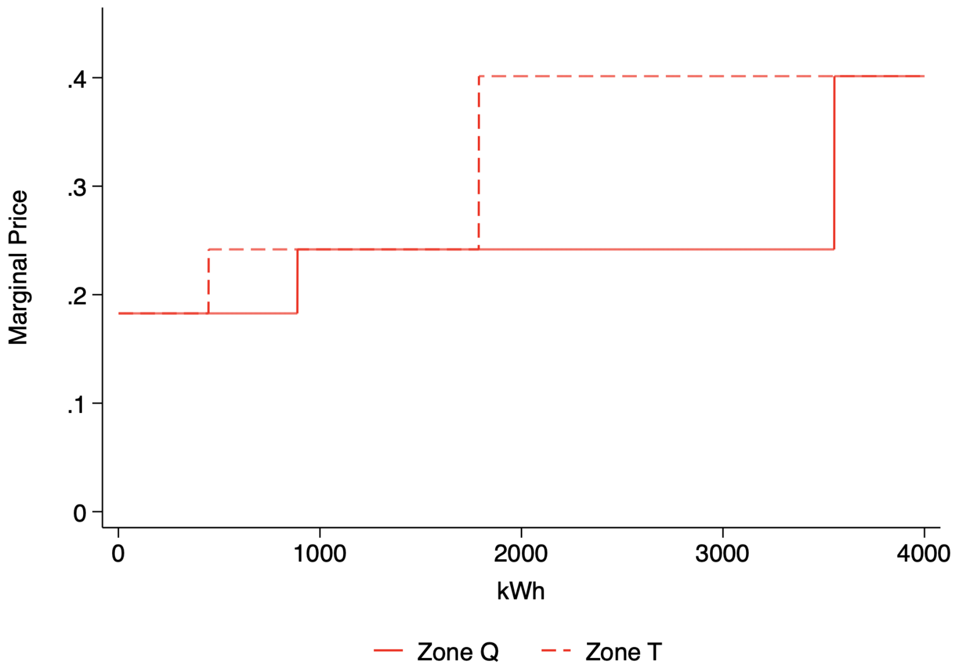
Note: This figure shows the level of baselines over time for each baseline territory and for households with electric heat in summer and winter. Data are shown from 1995 to 2020, as this is the period for which public data is available.

To determine the level of each baseline, PG&E set quantities so that 50 to 60 percent of expected residential electricity consumption in each climate zone is set as "baseline" consumption (equivalently, so that 50 to 60 percent of consumption is in Tier 1)[9]. Figure 2 shows the daily baselines from 1995 to 2020 for each baseline territory within PG&E. There is a great deal of variation both across baseline territories and even within territories from summer to winter and between customers with electric versus gas heat. Over the course the sample for this study (2008 to 2020), baseline quantities change four times.

Because baseline territories are used to determine baselines and therefore marginal and average prices, and customers who live very close to one another might be assigned to different baseline territories, there is variation in the prices faced by customers close to the baseline territory borders.

[9]One might be concerned that this could lead to endogeneity, where the actions of a household impact the baseline allowance in future periods. I assume that individual households do not exhibit market power, an assumption supported by the fact that each baseline territory contains at least 6,000 households.

Figure 3: Price variation in Territory Q versus Territory T

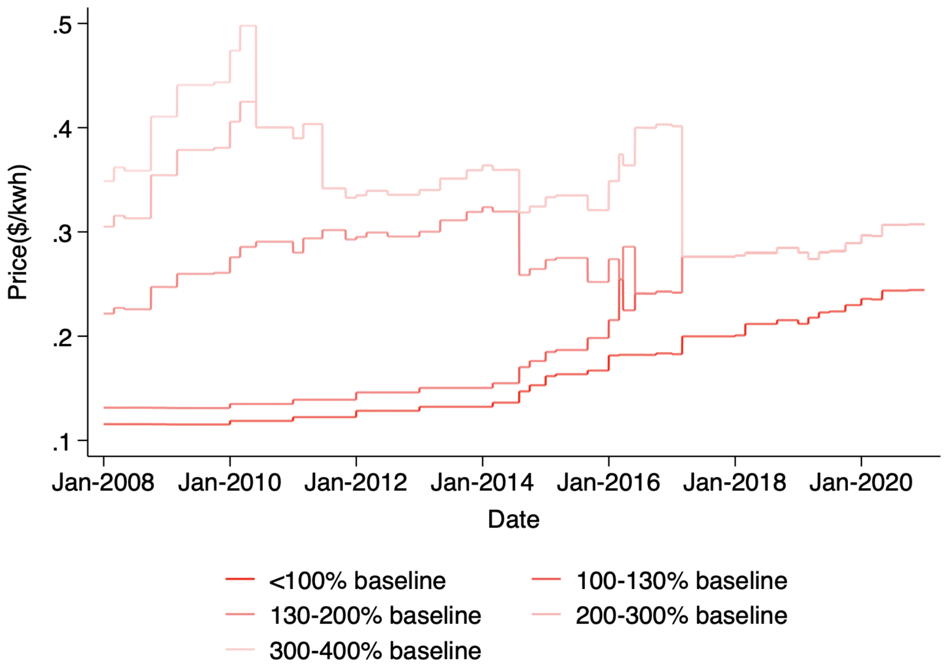


Note: This figure shows the marginal price path for baseline territory Q compared with baseline territory T in January 2017 for customers with electric heat. Territories Q and T are directly adjacent to one another.

Returning once more to the illustrative example, recall that Customer B (in Territory T) face a monthly bill \$26 higher than Customer A (in Territory Q) for the identical level of usage. Because Territories T and Q are divided by an elevation discontinuity, these two customers might live in the same neighborhood, face the same climatic conditions, and still face substantially different monthly bills. Figure 3 exhibits the full price schedule faced by customers in Territory Q compared with T during the winter months of 2017.

Note that the existing literature, including Ito (2014) and Shaffer (2020), often use utility service territory boundaries as a source of exogenous spatial price variation. Utility service territory boundaries, however, are vulnerable to confounding non-price factors along the utility border, such as utility-specific programs and potential household selection effects. Because baseline territories boundaries are within a single utility's service territory, they are not subject to the same confound-

Figure 4: PG&E price evolution over time



Note: This figure shows the price schedule over time for PG&E's standard default non-time varying tariff (Tariff E-1) from 2008 to 2020. The darkest line shows marginal prices for the lowest level of usage over time (under 100% of the baseline), while lighter shades show marginal prices for higher levels of usage.

ing effects to prices. Furthermore, utility service boundaries are often limited to only a narrow geographic range. PG&E's baseline territories cover a much broader spatial area, allowing for a more diverse set of households that may be more representative of the broader population.

Not only do marginal prices vary spatially across baseline territory borders, but there is a great deal of price variation over time as well. Figure 4 shows the evolution of each price over time for the standard residential tariff, E-1. Note that not only is there price variation within each tier, but there is a compressing of tiers that occurs in December 2016, when rate E-1 moves from four tiers to three. This provides useful identifying variation over time, that can be used in combination with the spatial variation resulting from climate zone boundaries.

With variation in baselines across both space and time, it's important to consider exactly what variation in baselines comes from each source of variation. In Table 1, I decompose the variation in

baseline territories according to space and time, by using baseline territory and month of sample fixed effects, along with controls for the other determinants of baselines – electric versus gas heating and summer versus winter. Column 1 shows how much of the variation in baselines can be explained by controls alone, while Columns 2 through 4 add spatial and time series fixed effects sequentially to demonstrate the extent to which each type of fixed effect explains variation in the baseline. The vast majority of variation in baselines not accounted for by the controls can be explained by spatial fixed effects, with a small amount explained by temporal fixed effects, suggesting that cross-sectional variation plays a major role in creating price differences. It is also worth noting that, as expected, almost all variation in baselines (99%) can be explained by spatial and temporal fixed effects in combination with controls for the other determinants of baselines.

2.2 Measures of heterogeneity

When estimating how consumers respond to prices, one critical component is to understand who is responding. Many papers, including Shaffer (2020) and Alberini, Gans and Velez-Lopez (2011) show there are significant heterogeneities in how customers respond to prices in their energy choices, driven by factors including information, salience, access to capital, and more. Different responses across customer groups induces heterogeneity in welfare changes. While in theory, transfers could be used to equitably redistribute any gains (or losses) from a policy, work by Sallee (2019) emphasizes the challenge that targeting presents, especially in the context of energy policy. In a context with limited transfers, understanding these mechanisms and heterogeneities is highly important for designing and evaluating policy, especially when equity is a policy objective.

In this setting, the primary demographic variable of interest is income. Because adoption of durable goods requires access to capital, we might expect that higher income customers are more likely to invest in durable goods that impact long-run price responsiveness. On the other hand, past

Table 1: Baseline variation decomposition

baseline_{it}	(1)	(2)	(3)	(4)
R^2	0.70	0.93	0.75	0.99
ElectricxSummer FE	Yes	No	No	No
ElectricxSummerxBT FE	No	Yes	No	No
ElectricxSummerxMofS FE	No	No	Yes	No
ElectricxSummerxBTxMofS FE	No	No	No	Yes

Notes: This table shows the results of four regressions, all with the length of baseline as the dependent variable. The level of observation is a customer account by month of sample.

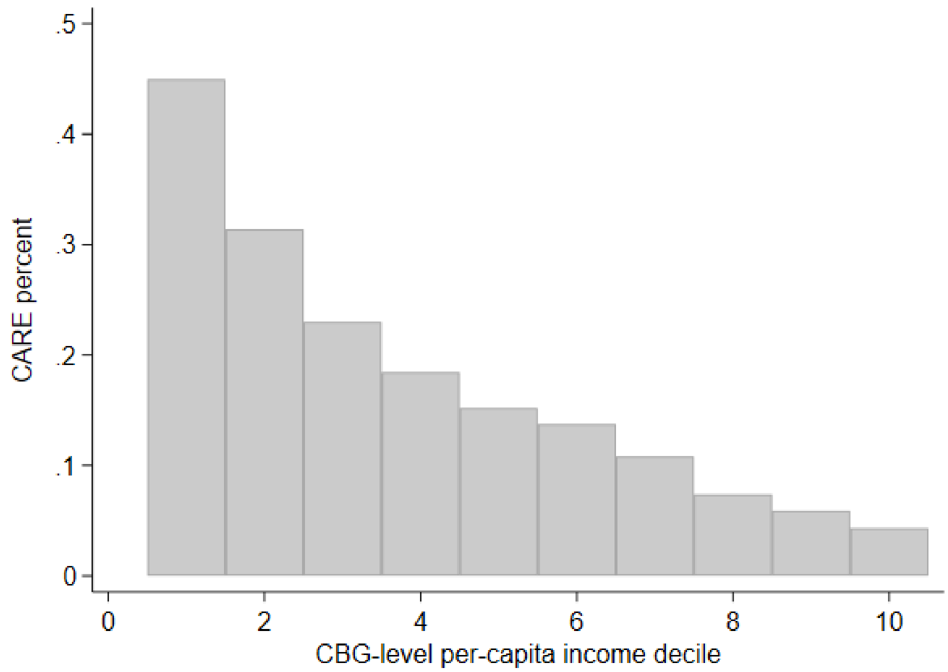
work (Alberini, Gans and Velez-Lopez, 2011; Reiss and White, 2005) seems to indicate that low-income consumers tend to be more aware of their bills and may therefore may be more responsive to price fluctuations, especially in the short-run.

While I do not directly observe income at a customer level[10], there are two primary ways that I explore demographic heterogeneity. First, I use CBG-level data on income from the 2017 5-year American Communities Survey to compare high-income CBGs with lower-income CBGs. Census data has numerous measures of income; my preferred measure in this work is average per-capita income.

Second, I use a proxy for income that is observed at the account-level: participation in the California Alternative Rates for Energy (CARE) program, following Auffhammer and Rubin (2018) among others. CARE is a program that is available to all energy customers in the state of California with incomes below 200% of the federal poverty level (FPL). Customers enroll directly through PG&E, who conducts random income verification checks to ensure that customers are compliant with the income requirements. PG&E estimates that 95% of eligible customers are enrolled in CARE. While there is some endogeneity in which customers are enrolled in CARE that may be correlated with information and bill attention, the high participation rate of CARE implies that it

[10]There are two reasons that I don't observe income: (1) high-quality income data at a consumer level are extremely difficult to access; and (2) utility data is anonymized, so that I couldn't match my data with an external income dataset, even could access it.

Figure 5: CARE enrollment versus CBG-level per-capita income decile



Note: In this figure, the horizontal axis is a measure of CBG-level per-capita income, while the vertical axis represents the proportion of households enrolled in CARE within a CBG.

is a good proxy for income.

In Figure 5, I compare how CARE participation correlates with CBG-level income deciles. While there is strong correlation between CARE enrollment and the CBG-level per-capita income, there is substantial heterogeneity in income levels within each CBG. There are numerous CARE enrollees across all CBGs, including those with the highest levels of per-capita income. Throughout the paper, CARE will be used as the primary proxy for income, while heterogeneity across federal poverty line deciles will be shown in the Appendix.

3 Data

For this study, I use account-level billing data for a subset of PG&E electricity customers from 2008 to 2020[11]. Included in the sample are all households living in Census Tracts with at least 15 premises present in multiple different baseline territories. This sampling restriction ensures that I have good balance to facilitate comparisons across a pricing border. Under this sampling restriction, I retain 463,000 premises, or about 9.6% of premises in PG&E's service territory. I observe data at the monthly level on electricity usage[12], billing, and adoption of durable goods (e.g. solar panels, electric heat, energy efficiency), as well as address and some limited demographic information. I merge PG&E's data with census data from the 2017 5-Year American Community Survey (ACS) to obtain demographic information. In my sample, there are an average of 588 households in each CBG.

In addition, I use daily weather data from the National Oceanic and Atmospheric Administration. The dataset, called Global Historical Climatology Network, reports daily temperatures for land surface stations across the globe. I use PG&E address data to determine the closest weather station to each household in the sample. For each billing period from 2008 to 2020, I determine the number of Heating and Cooling Degree Days[13] at the nearest weather stations for a particular household, then merging those figures directly into the billing data.

In my empirical analysis, I restrict my sample in several ways: first, I omit households with non-standard baselines such as medical baselines. Second, for consistency across bills, I include only bills ranging between 28 and 33 days. Third, because baselines change over the course of

[11]PG&E has granted me access to this data under a confidentiality agreement

[12]The electricity usage data that I use throughout this paper is *net* monthly electricity consumption. For solar customers who both generate and consume electricity, their net consumption is the difference between their gross monthly consumption and their gross monthly generation.

[13]Heating degree days and cooling degree days are common measures of how hot or cold are region is across a period of time. In particular they provide a measure of the distance from a standard neutral indoor temperature (65 degree Fahrenheit). Cooling degree days are calculated according to the following formula: $\sum_{M_i}(\text{Daily Mean Temperature}_i - 65)$ where M_i refers to the monthly billing period for each household i., while heating degree days as calculated as $\sum_{M_i}(65 - \text{Daily Mean Temperature}_i)$.

the sample, there are some geographic areas which have higher baselines than their neighbors at some point in the sample and lower baselines than their neighbors at other points. I drop these observations, ensuring that I only include households who are consistently in the “high” or “low” price region throughout the sample. After making these sampling restrictions, I retain 219,000 premises and 524,000 accounts.[14]

In Table 2, I present summary statistics. I show the means and standard errors for my sample, along with the number of utility accounts for each variable. For comparison, I show a select group of variables that I observe for the full set of PG&E residential customers (4.8 million premises and 21 million accounts) from 2008 to 2020. The sample in this study seems to be fairly representative of the broader PG&E population in the share of customers adopting electric heat and solar and enrolling in CARE. However, the average customer in this sample faces baselines that are 19% higher than in the broader PG&E population and consumes 26% more electricity.

4 Research Design and Results

While a vast number of papers have quasi-experimentally estimated short-run price elasticities of demand for residential electricity customers, very few have done the same in the long run. In the short and medium run, I follow the existing literature, relying on price variation over time and across space using panel methods. In the long run, however, I employ a new approach, leveraging a novel source of persistent and long-lasting cross-sectional price variation. In this section, I describe my empirical approach and results in the long run. I then anchor my results within the existing literature by using standard methods to estimate short-run price elasticities of demand. In the Appendix, I explore the dynamics of consumers’ price responses by extending the short-run approach to the medium-run.

[14]Note that many more accounts exist than premises. This is because most premises have multiple different account-holders over the course of the 13-year sample, due to customers moving to new premises.

Table 2: Summary statistics

	In Sample		
	Mean	Std.Dev.	Accounts
Marginal price (dollars per kWh)	0.20	0.08	523,927
Average price (dollar per kWh)	0.22	0.51	519,963
Monthly baseline (kWh)	415.45	494.87	523,927
Monthly consumption (kWh)	497.01	833.64	523,927
Percent electric heat	0.23	0.42	523,927
Percent solar	0.04	0.20	523,927
Percent CARE	0.22	0.41	523,927
Average Daily Heating Degree Days	7.69	5.27	523,219
Average Daily Cooling Degree Days	2.39	3.08	523,219
Per-capita Income	40097.17	20843.70	523,927
Account length (months)	31.66	42.00	523,927
	All PG&E		
	Mean	Std.Dev.	Accounts
Monthly baseline (kWh)	349.19	427.85	21,390,754
Monthly consumption (kWh)	395.34	644.39	21,411,577
Percent electric heat	0.21	0.40	21,445,946
Percent solar	0.03	0.18	21,445,946
Percent CARE	0.25	0.43	21,445,946

4.1 Long run empirical strategy and results

To estimate price elasticities of demand, economists typically leverage price variation over time and estimate how consumers react to dynamic changes in the price schedule. However, this type of analysis is limited in that it only captures certain margins of response among certain customers. First, it only captures customers who are continuously present in the sample over a long period of time. However, electricity usage and price responses may vary substantially across housing age and tenure. Furthermore, as recent work by Davis (2020) suggests, important durable good decisions such as whether a home is heated by gas or electricity may often be decided when a home is built, with substantial switching costs that lead to low incidence of switching behavior. Alternatively, investment decisions may be made when a utility account switches due to a new owner or tenant moving in. The typical dynamic methods used in the literature to estimate elasticities often fails

to capture the variation in recently-built or recently-renovated homes – in fact, any approach that relies on price changes over time will fail to capture this critical margin of response.

The challenge, then, is determining how to estimate differences in consumption without a "pre-period". Instead of leveraging price changes over time, I leverage cross-sectional differences in prices due to baseline territory divisions to observe long-run differences in durable good adoption and consumption.

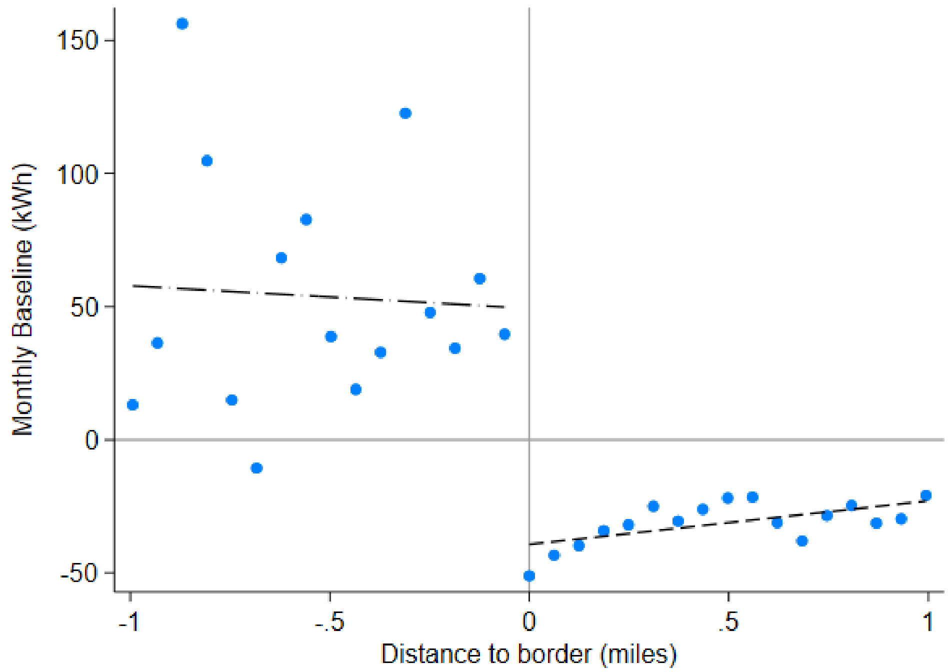
The baseline territory boundaries divide PG&E's service territory into a series of high price and low price regions. Because these boundaries are often drawn according to elevation discontinuities that separate from any other administrative boundary, households are similar in expectation on either side of the border except for the difference in baseline (and therefore price) that they face. Importantly, I restrict my sample to borders where the ordering of baselines has remained consistent across the boundary since the start of my sample in 2008. To estimate a long-run elasticity, I leverage this cross-sectional price variation with a regression discontinuity approach.

Throughout the main body of the paper, I assume that households response to average variable prices[15] rather than marginal prices. Past studies from Ito (2014) and Shaffer (2020), have found that households are unlikely to respond to marginal prices in increasing block pricing settings. In particular, Ito (2014) finds that households are more responsive to average variable prices than to marginal prices. In Section 4.2, I show that this finding holds in this setting as well and that at least in the short run, consumers are more responsive to average variable prices than marginal prices.

I begin by estimating how several important variables change across the baseline territory

[15]I use average variable prices rather than average prices due to nuances surrounding solar billing. Solar net metering customers are billed for the balance of their energy consumption once per year, rather than on a monthly basis, leading to negative bills in most months and potentially a large positive bill in a single month. Average prices for these customers do not reflect their incentives and have the potential to create bias in the sample. Rather, I use average variable prices, which are identical for the vast majority of customers but reflect the true incentives for solar customers.

Figure 6: First stage RD - baseline

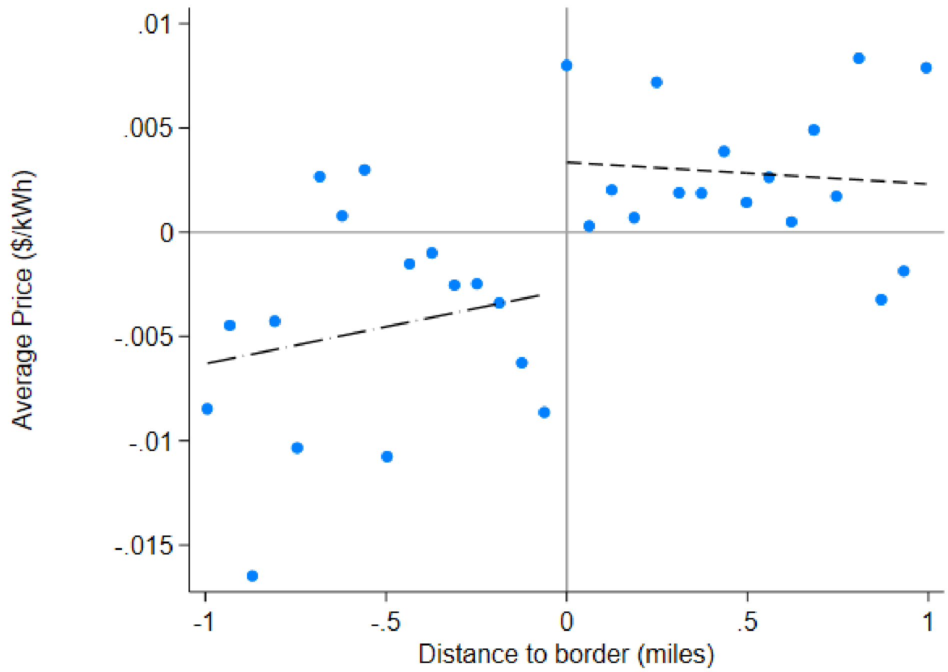


Note: In this figure, each dot represents all households within a 100-meter bin. The vertical axis shows residuals after regressing monthly baselines on CBG-by-month-of-sample and electric-heat-by-season fixed effects and taking the mean of the residual within each bin. The dotted lines are lines of best fit across all bins within a 1-mile bandwidth on either side of the baseline discontinuity.

boundary. To implement this approach, I restrict my sample to households within one mile of the baseline territory boundary. For each variable of interest, I regress on CBG-by-month-of-sample and electric-heat-by-season fixed effects, taking the means of the residuals across 100-meter bins. I then estimate local linear regressions across all bins on each side of the border, plotting the line of best fit. The results are shown in Figures 6, 7, and 8.

First, to establish that baselines vary across the border as expected, Figure 6 plots the magnitude of daily baselines against the distance to the border. There is a clear discontinuity at the border with magnitude of approximately 90 kWh, demonstrating that baselines are significantly impacted by the border discontinuity. This difference in baselines impacts prices, as shown in Figures 7. While there is more noise in these regressions since marginal and average variable prices are endogenous

Figure 7: First stage RD - average variable price



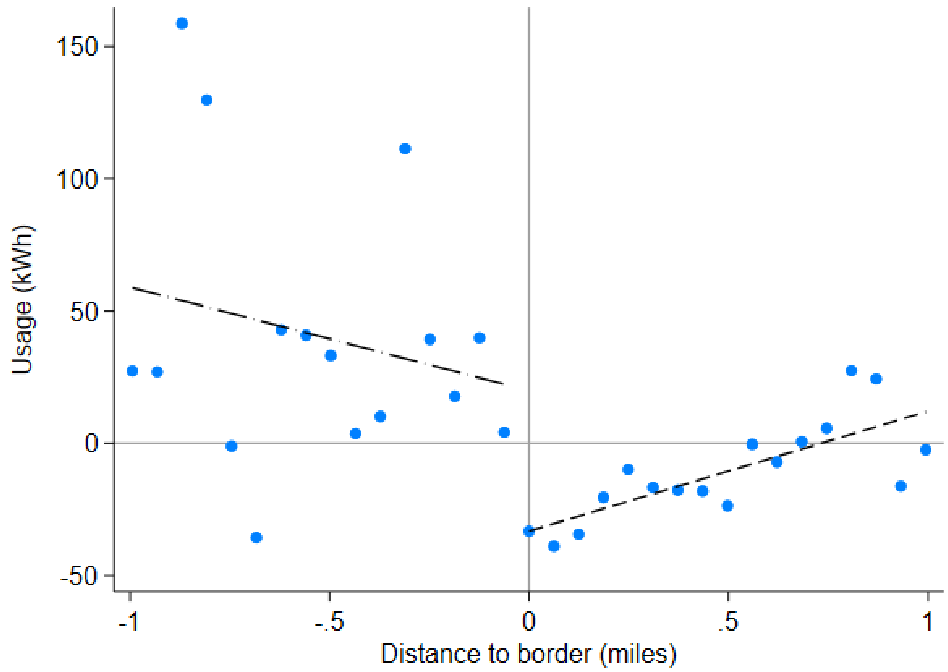
Note: In this figure, each dot represents all households within a 100-meter bin. The vertical axis shows residuals after regressing average variable price on CBG-by-month-of-sample and electric-heat-by-season fixed effects and taking the mean of the residual within each bin. The dotted lines are lines of best fit across all bins within a 1-mile bandwidth on either side of the baseline discontinuity.

to consumption, there is a clear impact at the border, where households with lower baselines face higher marginal prices and average variable prices, by an average of 2.8 and 1.6 cents per kWh respectively. At median levels of electricity usage, this difference in price would imply a bill difference of about $10.80 per month.

Next, I show that this variation in prices causes changes in electricity consumption. Figure 8 shows a reduced form regression, where monthly electricity consumption on the "high price" side of the border is about 200 kWh lower than electricity consumption on the "low price" side of the border.

To confirm that these results are not driven by temperature-related factors, I run falsification tests on heating degree days, and cooling degree days after conditioning out CBG-by-month-of-

Figure 8: Reduced form RD

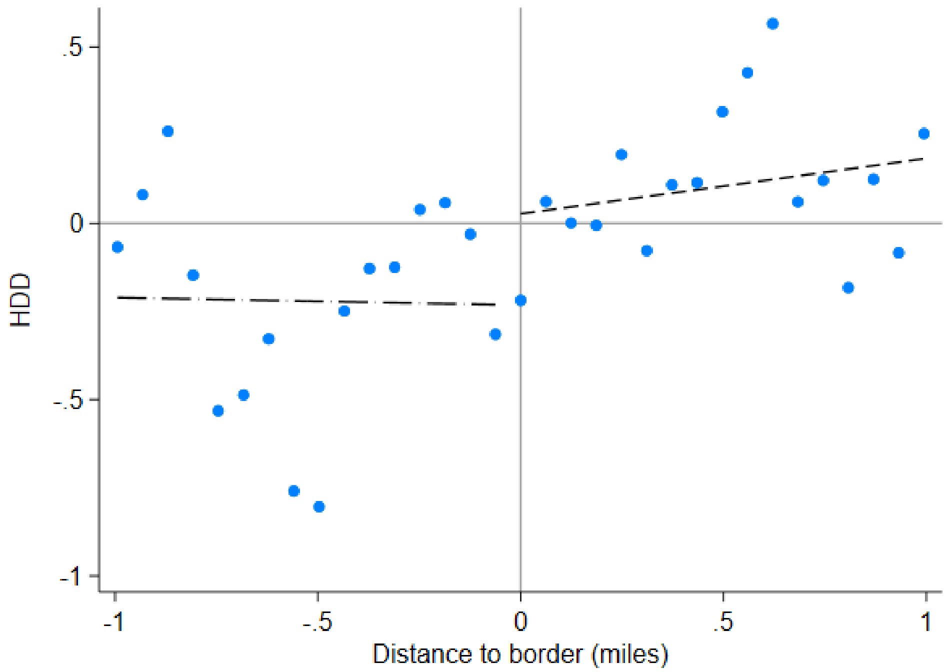


Note: In this figure, each dot represents all households within a 100-meter bin. The vertical axis shows residuals after regressing monthly electricity consumption on CBG-by-month-of-sample and electric-heat-by-season fixed effects and taking the mean of the residual within each bin. The dotted lines are lines of best fit across all bins within a 1-mile bandwidth on either side of the baseline discontinuity.

sample and electric heat fixed effects. Results of each of these falsification tests are shown in Figures 9, and 10.

With variation in baselines leading to persistent differences in prices across a long period of time, and those persistent price differences leading to differences in consumption, this is a natural setting to estimate a long-run price elasticity of demand. However, an important consideration when estimating elasticities in an increasing-block-pricing setting is that prices are endogenous to consumption. As customers use more electricity, the marginal price of electricity increases, meaning that the marginal price of electricity is correlated with consumption. To solve this issue, I use an instrumental variables approach, instrumenting for price with the length of the baseline. Within a narrow bandwidth of the baseline discontinuity of one mile, the only mechanism through which

Figure 9: Falsification test - HDDs



Note: In this figure, each dot represents all households within a 100-meter bin. The vertical axis shows residuals after regressing average daily heating degree days on CBG and electric-heat fixed effects and taking the mean of the residual within each bin. The dotted lines are lines of best fit across all bins within a 1-mile bandwidth on either side of the baseline discontinuity.

the baseline impacts electricity consumption is through prices.

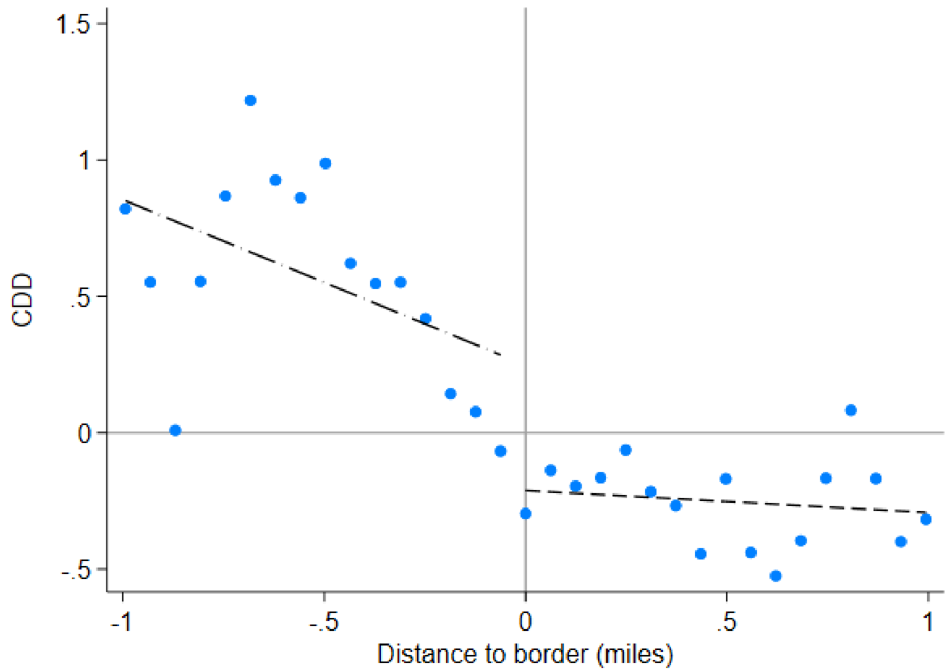
Leveraging this approach combining a regression discontinuity and two-stage-least-squares, I run the following regressions:

$$\text{First stage: } ln(p_{it}) = \alpha_0 + \alpha_1 \mathrm{Hi}_i + \alpha_2 \mathrm{d}_i + \alpha_3 \mathrm{d}_i \mathrm{Hi}_i + \gamma_{ct} + \eta_{e_s} + \epsilon_{it} \tag{1}$$

$$\text{Second stage: } ln(z_{it}) = \beta_0 + \beta_1 \widehat{ln(p_{it})} + \beta_2 \mathrm{d}_i + \beta_3 \mathrm{d}_i \mathrm{Hi}_i + \gamma_{ct} + \eta_{e_s} + \epsilon_{it} \tag{2}$$

where c identifies Census Block Groups, e is a dummy variable indicating if a customer has electric heat, s denotes whether the bill is in the summer or winter, z_{it} represents electricity consumption for household i in month t, p_{it} denotes the contemporaneous average variable price, d_t denotes the running variable in the regression discontinuity – the distance (in meters) between the household

Figure 10: Falsification test - CDDs



Note: In this figure, each dot represents all households within a 100-meter bin. The vertical axis shows residuals after regressing average daily cooling degree days on CBG and electric-heat fixed effects and taking the mean of the residual within each bin. The dotted lines are lines of best fit across all bins within a 1-mile bandwidth on either side of the baseline discontinuity.

and the baseline territory boundary, and ϵ denotes an idiosyncratic error term.. CBG-by-month-of-sample fixed effects are included to control for variation in demographic traits that may change over time. Electric-heat-by-summer fixed effects are included since baselines vary according to heating type and season. Standard errors are clustered according to baseline territory, since prices are assigned at the baseline territory level, and month-of-sample, to account for unobserved correlation in variances across seasons and over time. The identifying assumption under this regression is that customers living close the baseline territory border with the same type of heating systems would consume similar amounts of electricity absent the differences in prices driven by baseline territories.

Because an indicator for electric heat is included in the fixed effects, this specification makes a parametric correction for heating type, as the length of a baseline is partly determined by heating

Table 3: Long-run first stage regression on average variable price

	1 mile	1/2 mile	2 miles
hi	0.017***	0.016***	0.019***
	(0.0018)	(0.0017)	(0.0020)
Distance to border	-0.0000022*	-0.0000010	0.000000012
	(0.0000011)	(0.0000010)	(0.00000078)
Hi x Distance	0.0000076***	0.000010***	-0.00000018
	(0.0000015)	(0.0000011)	(0.0000016)
Observations	7395980	5646913	9020224

Note: Fixed effects include CBG-by-month and electric-heat-by-season. Standard errors are clustered by baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.

type. This is a necessary fixed effect to prevent an endogenous heat type choice to bias the estimates. However, the inclusion of this fixed effect eliminates heating choice as a potential mechanism to impact consumption. Therefore, the long-run elasticity estimated here is a lower bound, as a theoretical specification that allowed a heating type margin to impact consumption would only increase the estimated elasticity.

The results of these regressions are shown in Tables 19, 4, and 5. In Table 19, I show the results of the first stage regressions on average variable price, in Table 4, I show reduced form results on monthly electricity consumption, and in Table 5, I show the IV long-run elasticity estimates. The first stage results show that crossing the baseline territory boundary leads to an average increase of 1.6 cents per kWh. At median levels of electricity usage, this difference in price would imply a bill difference of about $8.64 per month. Meanwhile, the reduced form estimates show that for the same change in monthly baseline, consumers respond by decreasing their consumption by about 200 kWh per month, or over 37% of the mean monthly usage.

As shown in Table 5, the IV regression results in an elasticity of -2.4, implying that customers are highly responsive to price changes in the long run. While this estimate is substantially larger than the existing literature, there are several reasons that one should expect a larger estimate in

Table 4: Long-run reduced form regression on monthly electricity consumption

	1 mile	1/2 mile	2 miles
hi	-228.5**	-207.6**	-227.4**
	(82.2)	(82.1)	(80.3)
Distance to border	-0.025	-0.066	0.00061
	(0.042)	(0.067)	(0.025)
Hi x Distance	0.031	0.074	-0.022
	(0.052)	(0.092)	(0.025)
Observations	7463542	5694337	9107026

Note: Fixed effects include CBG-by-month and electric-heat-by-season. Standard errors are clustered by baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.

this setting and under this methodology: first, the existing literature tends to use panel methods that compares consumption for a customer before and after a price change. This type of estimation misses important margins of response – specifically investment decisions at the time that a home is built or when a utility account changes due to a new owner or tenant moving in. By leveraging a persistent source of cross-sectional price variation, the specification here captures the investment margin, including in new and recently transacted homes, both of which are often missed by studies that rely primarily on price variation over time, as opposed to across space.

Second, there are very few existing quasi-experimental estimates of long-run elasticities in the literature. Most estimates rely on strong structural assumptions made by researchers. One of the only quasi-experimental long-run elasticity estimate to date, Deryugina, MacKay and Reif (2019), looks only at a time horizon up to three years, and estimates elasticities using the panel methods described above, which are likely to miss important margins of response. The estimates in that paper should be compared to the medium-run results shown previously in this paper, not these long-run estimates, because of the parallels in both time horizon and in the identifying variation. The other quasi-experimental long-run elasticity estimate to date, Feehan (2018), finds a long-run

Table 5: Long-run IV estimate of elasticity (average variable price)

	1 mile	1/2 mile	2 miles
Log Average Price	-2.25***	-2.39***	-1.95***
	(0.56)	(0.56)	(0.57)
Distance to border	-0.00012***	-0.00014***	-0.000030
	(0.000035)	(0.000023)	(0.000023)
Hi x Distance	0.00026***	0.00036***	0.0000079
	(0.000051)	(0.000073)	(0.000038)
Observations	7327914	5599033	8932262
F	62.3	57.3	68.6

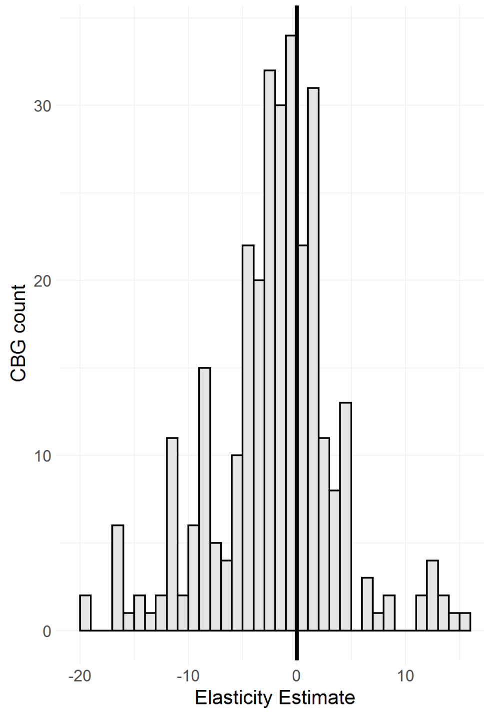
Note: Fixed effects include CBG-by-month and electric-heat-by-season. Standard errors are clustered by baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.

elasticity of -1.2 in Newfoundland and Labrador, Canada. Critically, the setting for this paper is in a different climate. Consumers in Newfoundland and Labrador face lower temperatures than California year-round, leading to less flexibility in decisions around heating and cooling. Furthermore, solar irradiance and air conditioner adoption is substantially lower, diminishing the value of some of the most important margins of long-run response observed in California. With additional margins of response and more flexible heating and cooling loads, one would expect consumers to be much more responsive to prices in this setting.

In Appendix A.2, I include several robustness checks. First, I show that varying the bandwidth of the regression discontinuity does not meaningfully change the results. Next, I estimate similar regressions under different parametric assumptions. While my main specification specifies linear effects on either side of the discontinuity, I show that using a quadratic or flat function has little impact on the results.

In addition, one might be concerned about endogeneity in this specification – when a customer adopts a durable good such as solar, their net electricity usage decreases dramatically, often putting them into a different pricing tier and decreasing both their marginal and average prices. Because

Figure 11: Histogram of long-run elasticity distribution across Census Block Groups

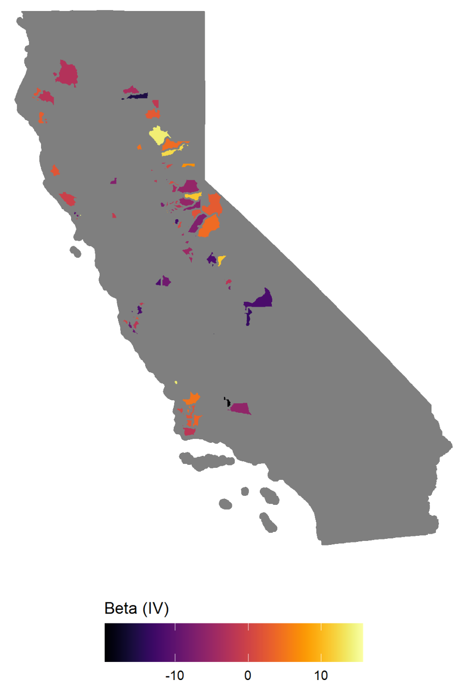


Note: This figure shows the results of estimating long-run elasticities within each Census Block Group. The histogram shows the distribution of CBG-specific elasticity estimates. CBGs with elasticities below -20 or above 20 have been omitted for scaling purposes.

I use the contemporaneous average variable price as the variable of interest, there is a concern that endogenous adoption of durable goods may decrease the price difference on either side of the border, thereby biasing upwards the estimated of elasticity. In Appendix A.2.3, I test alternative definitions of price, where prices are determined by consumption levels in a baseline year, finding similar long-run elasticity estimates.

One may also be concerned that this result is driven by the presence of outliers. To rule out this possibility, I separately estimate coefficients for every Census Block Group in the sample. As shown in Figure 11, I find that 52% of CBGs exhibit elasticities between 0 and -10, and that the few outliers that do exist are not the primary factor driving the results. In Figure 12, I explore the distribution of elasticity estimates across space, finding no demographic trends that are predictive of the elasticity magnitude.

Figure 12: Map of long-run elasticities by Census Block Group



Note: This map shows the results of estimating long-run elasticities within each Census Block Group. The color of each CBG on the map indicates the long-run elasticity estimate for that CBG. CBGs with elasticities below -20 or above 20 have been omitted for scaling purposes.

4.2 Short run estimation

In this section, I anchor these results within the existing literature by estimating short-run elasticities, which are much more commonly estimated. in contrast with my long-run approach, in the short run, I follow standard methods including Ito (2014). I rely on three primary sources of identifying variation: (1) spatial discontinuities in the baseline and therefore price that a customer faces; (2) temporal variation in prices; and (3) temporal variation in baselines[16]. In combination, these three sources of variation lead to prices that vary both in time and across space.

I follow the methodology presented by Ito (2014) in order to estimate short-run responses to both average and marginal prices. In that 2014 paper, Ito leverages similar variation in prices over

[16]Because month-of-sample fixed effects are included in all specifications, temporal variation in baselines is limited to policy changes and does not include seasonal variation.

time and along a spatial discontinuity to estimate short-run elasticities.

Let c_{it} denote consumption for customer i in month t and AP_{it} denote the average variable price that customer i faces in month t. For expositional purposes, I assume that all customers respond to average variable price, though I will test this assumption later in this section. Typically, one could consider the following first differences estimating equation:

$$\Delta\ln(c_{it}) = \beta_1 \Delta\ln(AP_{it}) + \gamma_{ct} + \eta_{it} \tag{3}$$

where $\Delta\ln(c_{it}) = \ln(c_{it}) - \ln(c_{i,t-12})$ is the difference between log consumption today and the same month one year prior, $\Delta\ln(AP_{it}) = \ln(AP_{it}) - \ln(AP_{i,t-12})$ is the difference between log marginal price today and the same month one year prior, γ_{ct} denotes CBG-by-time fixed effects, and $\eta_{it} = \epsilon_{it} - \epsilon_{i,t-12}$ is an idiosyncratic error term. Using this first differences estimator removes household-by-month-of-year variation. However, the structure of electricity rates in California raises issues for this estimation.

As described in the background section, electricity providers in California employ increasing-block pricing. Hence, as customers use more electricity, the marginal price of electricity increases. The marginal price of electricity is therefore correlated with consumption, meaning that in the Equation (1), the marginal price is correlated with the unobserved error term η_{it}.

To solve this issue, I follow Ito (2014). Ito instruments for price using the policy-induced price change. The instrument, called a simulated instrument in the tax literature, is

$$\Delta\ln(AP_{it})^I = \ln(AP_t(c_{i,t-6})) - \ln(AP_{t-12}(c_{i,t-6})) \tag{4}$$

This instrument isolates the change in price induced by exogenous policy change at a specific consumption level. For it to be valid, $c_{i,t-6}$ must be uncorrelated with the unobserved error η_{it}.

Some past studies have used the base year consumption, $c_{i,t-12}$, here. However, as Ito points out, mean reversion presents a challenge in this setting, as transitory shocks to consumption in month $t-12$ will cause mean reversion in consumption that will be correlated $\epsilon_{i,t-12}$ and therefore η_{it}. Blomquist and Selin (2010) and Saez, Slemrod and Giertz (2012) suggest that in an income tax setting, using consumption in a period midway between t and $t-12$ can be used to address this mean reversion problem.

This instrument might still be correlated with η_{it} if specific types of electricity users (e.g. high- and low-usage customers) have different consumption paths over time. This is where I make use of the border discontinuity that results from baseline territories. Ito uses the border discontinuity between utility regions. Here, I build on his approach by leveraging within-utility price variation driven by baseline territories. In different utility regions, there are often different incentives and marketing strategies for energy durable goods, such as solar and energy efficiency, that go beyond the price that customers face. Leveraging price variation across baseline territories allows me to isolate the price variation, without concern for these confounding factors. Furthermore, baseline territory borders are not limited to one concentrated geographic area as utility borders are, leading to a more representative sample.

To ensure that households across the baseline territory boundary are comparable, I restrict my sample to census block groups that have at least 50 service accounts in multiple different climate zones. The resulting identifying assumption is that customers in the same census block groups on either side of the climate zone boundary would consume the same amount of energy absent the price variation that results from the climate zones.

With this instrument, I estimate a two-stage least squares regression of consumption on average variable price, instrumenting for average variable price with the simulated instrument described

above:

$$\text{First stage: } \Delta\ln(AP_{it}) = \alpha_1\ \Delta\ln(AP_{it})^I + f_t(c_{i,t-6}) + \gamma_{ct} + \eta_{it} \tag{5}$$

$$\text{Second stage: } \Delta\ln(c_{it}) = \beta_1\ \widehat{\Delta\ln(AP_{it})} + f_t(c_{i,t-6}) + \gamma_{ct} + \eta_{it} \tag{6}$$

where $f_t(c_{i,t-6})$ is a set of dummy variables determined by the decile of consumption in period $t-6$. Formally, for percentile j, $f_{j,t} = 1\{c_{j,t-6} < c_{i,t-6} \leq c_{j+1,t-6}\}$. Standard errors are clustered according to household by month-of-sample.

In this specification, β_1 represents a short-run elasticity to average variable price – it estimates how any exogenous price change over the previous year leads to a difference in consumption within that period.

As Ito (2014) finds, customers might respond to average prices instead of marginal prices. To test this result in this setting, I include two additional short-run specifications: one in which marginal prices replace average variable prices as the primary covariates of interest, and one which includes both average variable and marginal prices as covariates. This final specification is called an encompassing test, and measures whether one pricing model "encompasses" the other. In his work, Ito (2014) finds that the average variable price model encompasses the marginal price model, implying that customers primarily respond to average variable prices rather than marginal prices.

As shown in Table 6, I find results that are consistent with the existing literature (Zhu et al., 2018). Elasticities are approximately -0.18 and -0.36 for marginal and average variable prices respectively. While I don't find that the average variable price model encompasses the marginal price model, customers seem to generally be more responsive to average variable prices than marginal prices.[17] As such, throughout the rest of the paper, my preferred specifications will use average

[17]Note that Shaffer (2020) finds a similar result, where customers are heterogeneous in how they respond to prices. I don't take a stand here on whether customers respond to marginal or average prices.

Table 6: Short-run price elasticity

	MP (1)	AP (2)	Encompassing (3)
$\Delta\ln(MP_{it})$	-0.18***		-0.052**
	(0.019)		(0.025)
$\Delta\ln(AP_{it})$		-0.36***	-0.28***
		(0.032)	(0.045)
Observations	5692238	5663639	5663639
F	480.9	989.7	99.8

Note: Across all columns, the dependent variable is $\Delta ln(c_{it})$. *Fixed effects include CBG-by-month and 6-month-lagged consumption deciles. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

variable prices as the primary covariate of interest with specifications showing marginal prices in the Appendix. These results primarily serve to anchor my results within the existing literature. Much of the literature on price elasticities in the residential electricity sector have focused on the short-run, and has typically found similar results to those that I present here – customers are more responsive to average variable price than to marginal price, but short-run responses to prices are relatively inelastic.

To understand how different types of consumers respond differently to prices, I use CARE as a proxy for income, as shown in Table 9. I estimate the same specification separately for CARE and non-CARE customers, finding that non-CARE (and therefore higher income) customers tend to be more responsive to prices than CARE customers. While there are some papers that find similar results (Brolinson, 2019; Schulte and Heindl, 2017), this result is in contrast with the majority of the literature, which finds that price elasticities of demand are higher among the poorer households (Alberini, Gans and Velez-Lopez, 2011; Reiss and White, 2005).

In Appendix A.7 I explore the dynamics of households' responses to price changes by estimating price elasticities in the medium run. While not the primary focus of this paper, these results provide some insight into how household behavior changes over time in response to prices.

Table 7: Short-run price elasticity by CARE

	CARE (1)	nonCARE (2)
$\Delta \ln(AP_{it})$	-0.20***	-0.43***
	(0.035)	(0.037)
Observations	1002596	4660937
F	605.7	1162.3

*Note: Across all columns, the dependent variable is $\Delta ln(c_{it})$. Fixed effects include CBG-by-month and 6-month-lagged consumption deciles. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

The comparison of short- and long-run elasticities suggests the likely channels through which consumers might respond. Because long-run responses are much larger than short-run responses, it is unlikely that these results are primarily driven by intensive margin changes, such as appliance use behaviors. The pattern of response is more consistent with adjustment along an extensive margin: the differential adoption of durable goods such as solar, energy efficiency, and air conditioning. In the next subsection, I empirically estimate how customers respond in their adoption of durable goods to better understand the specific mechanisms driving the observed long-run response.

5 Mechanisms

To this point, I have shown that residential electricity customers are highly responsive to electricity prices in the long run. This contrasts with the short run, where electricity consumption is relatively inelastic, as shown in Section 4.1 and in much of the literature. This begs the question of which mechanisms are driving this response. Are customers making *intensive* margin changes to their electricity consumption, by changing their behaviors surrounding heating or appliances? Or are they making *extensive* margin changes, by adopting durable goods such as solar, energy efficiency, or household appliances?

To better understand the primary drivers of these results, it's crucial to understand the specific

mechanisms through which customers respond to prices. The observed differences between short- and long-run elasticities suggest that investment in durable goods might play a significant role. I test for differences in durable good adoption in two ways: first, I directly test for differences in adoption for the two durable goods that I directly observe, solar and energy efficient appliances that are supported by PG&E incentive programs. Second, I test for differences in how electricity consumption responds to temperature across the baseline territory border, and explore heterogeneity.

5.1 Solar and energy efficiency programs

To understand how customers respond to prices with durable good investment in the long run, I estimate the following model, using a simple regression discontinuity approach:

$$\text{Adoption}_i = \beta_0 + \beta_1 \text{Hi}_i + \beta_2 \text{d}_i + \beta_3 \text{d}_i \text{Hi}_i + \gamma_c + \epsilon_i$$

where Adoption_i is a binary variable indicating whether a customer ever adopts the durable good over the course of the sample; Hi_i is a binary variable indicating whether customer i lives in the "high price" baseline territory within a CBG, d_i is a measure of distance from the baseline territory boundary, c denotes CBG, and ϵ_i denotes an idiosyncratic error term.

Similar to the long run price elasticities estimated in Section 4.1, the identifying variation in this specification is cross-sectional variation in prices driven by the baseline territory discontinuity. I show the graphs resulting from this regression specification.

In Figures 17 and 18, I show the results for the two durable goods of interest: residential solar adoption and utility energy efficiency programs. There is very little evidence of statistically significant changes in either solar adoption or energy efficiency adoption across the baseline territory

Table 8: Solar adoption

	Percent Solar
High Price	-0.013
	(0.0086)
Distance to border	-0.000011
	(0.0000064)
High Price x Distance	0.000018
	(0.000012)
Observations	272358

*Note: fixed effects include CBG and electric heat. Standard errors are clustered by baseline territory. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

Table 9: Energy efficiency adoption

	Percent EE
High Price	-0.0032
	(0.0028)
Distance to border	-0.0000011
	(0.0000015)
High Price x Distance	0.0000014
	(0.0000026)
Observations	272358

*Note: fixed effects include CBG and electric heat. Standard errors are clustered by baseline territory. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

border,[18]. In fact, the 95% confidence interval in the solar specification rules out a solar adoption effect of anything greater than 0.2 percentage points. These results effectively rule out solar and energy efficiency programs as mechanisms driving the observed long-run elasticities.

5.2 Temperature response

While there is little discernible impact of the price discontinuity on the adoption of solar and enrollment in energy efficiency programs, there are a number of other margins that may be driving the long-run consumption results. For instance, there may be other durable goods that are less easy to observe, such as air conditioning[19], where households' adoption patterns may vary with price.

[18]Note that the only observed energy efficiency measures are PG&E programs (e.g. utility-run subsidies for energy efficiency appliances and energy audits), which are only a portion of energy efficiency measures that households adopt in practice.

[19]Air conditioning is especially relevant in California, where air conditioning adoption rates are among the lowest in the country at just 72%

Furthermore, on the intensive margin, consumers in different price regimes may behave differently in their appliance usage and where they choose to set their thermostats. While my data do not allow for direct testing of these mechanisms, in this section, I explore how consumers respond to temperature in an effort to learn more about the mechanisms contributing to the observed long-run price elasticities.

Specifically, I estimate the relationship between outdoor heat and electricity consumption, following the "degree day method" used by Thorpe (2013) and Fowlie, Greenstone and Wolfram (2018), among households in different price regimes. I obtain temperature data for all California weather stations from NOAA. For each household bill in my sample, I determine the closest weather station with complete temperature data at the time of the billing period to that household, and merge that temperature data into the billing data. I then use that temperature data to calculate the average daily heating degree days (HDDs) and average daily cooling degree days (CDDs) in order to normalize across billing periods of different lengths. To ensure comparability across price regimes, I restrict my sample to households within a 1-mile bandwidth of the baseline territory border.

To compare households' temperature responses, I estimate the following regression specifications. Limiting my sample to summer months (May to October), I estimate how electricity consumption responds to cooling degree days across the electricity pricing border. Similarly, I estimate how electricity consumption responds to heating degrees days across the electricity pricing border, restricting my sample to winter months (November to April).

$$\text{kWh}_{it} = \beta_0 + f(\text{CDD}_{it})\text{Hi}_i + \epsilon_{it} \text{ for months May to October} \tag{7}$$

$$\text{kWh}_{it} = \beta_0 + f(\text{HDD}_{it})\text{Hi}_i + \epsilon_{it} \text{ for months November to April} \tag{8}$$

In both specifications, kWh_{it} denotes electricity consumption for household i in month t, HDD_{it} and HDD_{it} refer to average daily cooling and heating degree days respectively, and Hi_i is an indicator for whether the household is on the "high price" side of the pricing border. $f(CDDit)$ is a flexible nonparametric function of cooling degree day bins. Specifically, $f(CDD_{it})$ is set of indicator variables determined by the number of cooling degree days for household i in period t. Each of these specifications uses Huber-White robust standard errors.

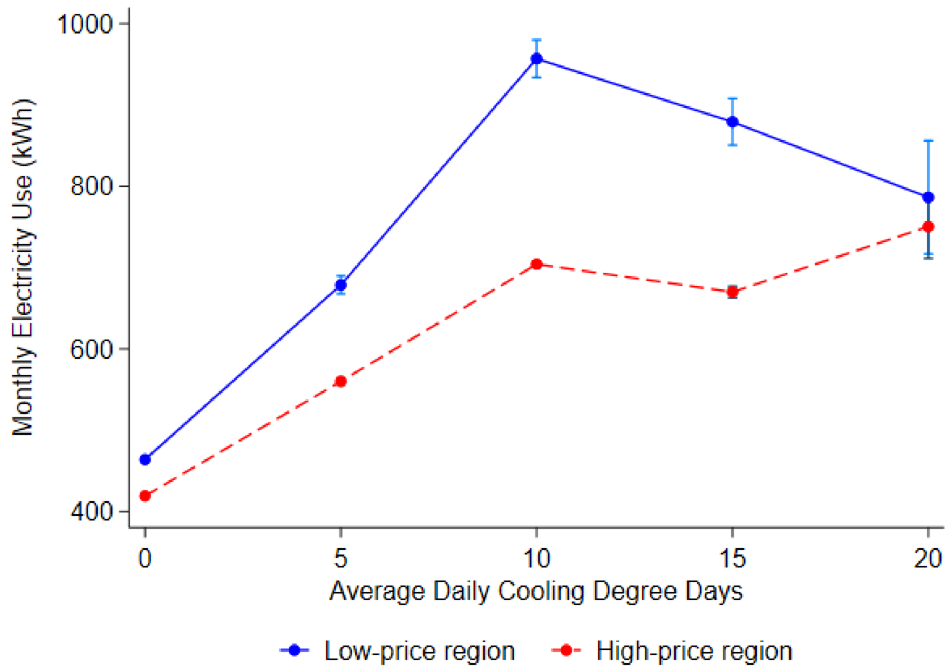
Results of these regressions are shown in Figures 13 and 14. First, I find that households facing higher prices have significantly flatter responses to both hotter weather in the summer and colder weather in the winter. In the summer, the differences in prices lead to consumption differences that generally rise at higher levels of cooling degree days. In the winter, the difference is especially prevalent for bills with between 15 and 25 heating degree days per day, before consumption decreases massively in the low price region.[20]

To understand this effect further, I break down these temperature differences by account longevity. I observe how long a utility account has been open at a particular household, and leverage this variable to estimate how a household's temperature response varies over time[21]. I separate observations into three bins: observations where the account is 0-2 years old (41% of observations), observations where account is 2-5 years old (30%), and observations where the account is over 5 years old (29%). Note that a single premise moves between bins when they reach each age threshold. As such, this analysis captures two separate effects: (1) learning and investment effects, where households change their behavior and/or investment decisions over time; and (2) compositional effects, where households that stay in the same premise for different tenures consume electricity differently.

[20]This effect is likely driven by differences in electric heat adoption among those households in the coldest summer regions of California.

[21]While there are several possible reasons that could cause account number and premise IDs to change (moving addresses, enrolling in a CCA, changing the account holder), for an account number to stay the same over time, a necessary condition is that the household is not moving to a new address.

Figure 13: Temperature response (summer)

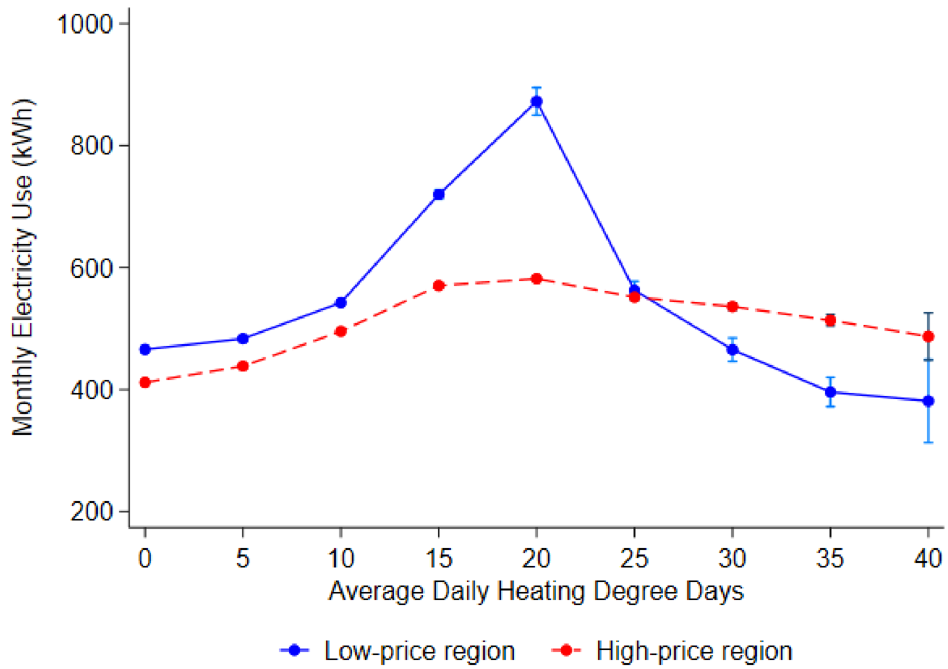


Note: This figure shows the results of regressing monthly electricity use on indicator terms for six different cooling degree day bins during summer, interacted with an indicator for whether a household is on the high or low price side of the border. This specification uses Huber-White robust standard errors.

Figures 15 and 16 show the results of this approach. While the winter heating effects are difficult to pick apart, there is a clear trend in summer cooling. Among low-price households in summer, observations where the account is older tend to have steeper temperature response curves, consuming more electricity on hotter days. However, among high-price households, there is little discernible difference in the cooling degree day response curves across account vintage. Meanwhile, in winter, the only clear pattern is that on very cold days, accounts with older vintages tend to consume less electricity.

These trends suggests different consumption patterns over time across pricing regimes. Low-price consumers make investments over time in goods that consumer a large amount of electricity during summer, while high-price consumers are much less likely to make similar investments. Meanwhile, in winter, the pricing differences seem to induce similar consumption differences across all

Figure 14: Temperature response (winter)



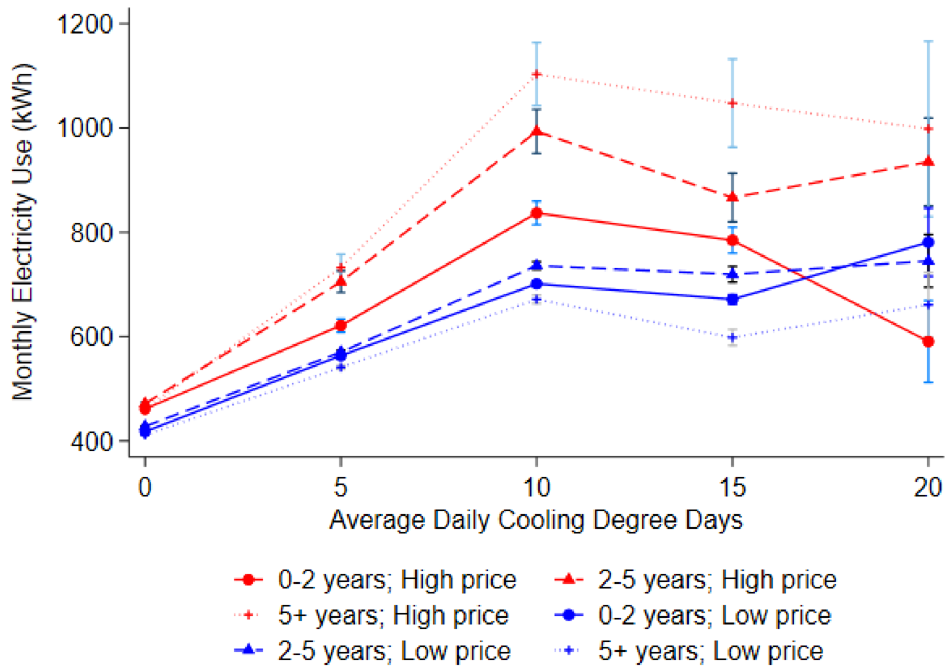
Note: This figure shows the results of regressing monthly electricity use on indicator terms for six different heating degree day bins during winter, interacted with an indicator for whether a household is on the high or low price side of the border. This specification uses Huber-White robust standard errors.

account vintages. While I don't observe appliance adoption directly, these trends seem to be most consistent with adoption of air conditioning, though it's also possible that these investments include other energy-intensive goods, such as home expansions and swimming pools.

These results follow a long literature estimating the temperature response of electricity consumption (Auffhammer and Mansur, 2014; Davis and Gertler, 2015; Kumar et al., 2020; Fazeli, Ruth and Davidsdottir, 2016; Auffhammer and Aroonruengsawat, 2012). The results here are broadly consistent with this literature – residential electricity consumption is U-shaped with respect to temperature, where very low temperatures and very high temperatures both lead to increases in electricity consumption. I build on this literature by showing compelling evidence that electricity prices are particularly impactful in how households respond to temperature variation.

Without appliance-level data, the results in this subsection are only suggestive. However, there

Figure 15: Temperature response by account length (summer)



Note: This figure shows the results of regressing monthly electricity use on indicator terms for six different cooling degree day bins during summer, interacted with an indicator for whether a household is on the high or low price side of the border and an indicator for the account's longevity. This specification uses Huber-White robust standard errors.

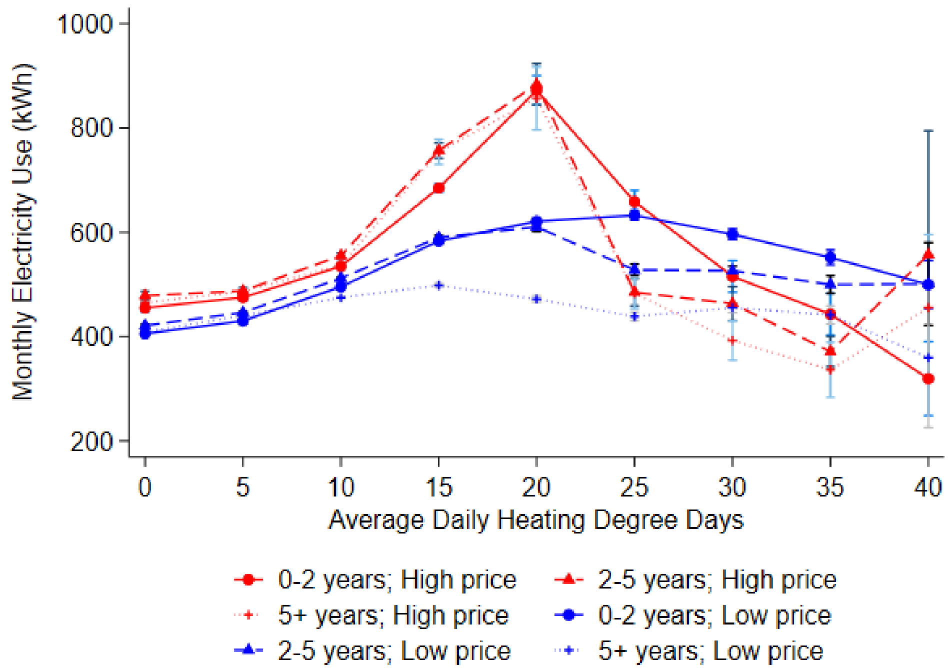
are clear trends in the data that warrant further investigation, and strongly suggest that cross-sectional differences in prices may lead to substantial differences in adoption of energy-intensive durable goods.

6 Heterogeneity in price responses

While I have established that consumers are highly responsive to electricity prices in the long run, it is important to understand what types of consumers are responsive and if heterogeneity exists. In this section, I explore heterogeneity in price responses, both in electricity consumption and in some of the mechanisms described in the previous section.

To begin, I estimate in Table 29 heterogeneity in elasticities according to per-capita income

Figure 16: Temperature response by account length (winter)



Note: This figure shows the results of regressing monthly electricity use on indicator terms for six different heating degree day bins during winter, interacted with an indicator for whether a household is on the high or low price side of the border and an indicator for the account's longevity. This specification uses Huber-White robust standard errors.

levels at the CBG level. To estimate this specification, I use an indicator variable to denote if a household is in a CBG above the median per-capita income level in my sample. I then run separate regressions for CARE and non-CARE customers, comparing price responsiveness across the two groups. For robustness, I include a specification using CBG-level income in Appendix A.5.

While in the short-run specification, higher-income consumers were more responsive, in the long run, lower-income consumers consumers are significantly more responsive. This is a somewhat surprising result – higher income consumers have more access to capital with which they can invest in durable goods that impact their consumption. High levels of price responsiveness among low-income households in the long-run indicates that there may be less capital intensive margins of response that low-income households are able to leverage. In Appendix A.6 I show that this result holds using CBG-level per-capita income as a proxy for CARE.

Table 10: Elasticity estimation by income

	CARE	non-CARE
Log Average Price	-8.43***	-2.35**
	(2.27)	(0.90)
Distance to border	-0.000023	-0.00015***
	(0.000082)	(0.000030)
Hi x Distance	0.000053	0.00029***
	(0.000073)	(0.000058)
Observations	1400825	5914069
F	64.7	131.6

*Note: This table shows two separate instrumental variable regressions by income of log consumption on price, instrumenting for price with distance to the baseline territory boundary. Income is proxied by whether a customer has ever enrolled in CARE. Fixed effects include CBG-by-month and a binary variable indicating electric heat. Standard errors are clustered by baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

In addition, while not the focus of this paper, in A.5 I show how consumption responds to price across several other demographic variables of interest at the CBG level, including homeownership, age of housing stock, race, and income inequality.

7 Conclusions

In this paper, I leverage a novel source of cross-sectional price variation estimate how residential electricity consumers respond to electricity prices in the long run. To anchor these results in the literature, I use standard methods to estimate elasticities in the short run. I find that consumers are much more price-responsive in the long run than the short run. The magnitude of this estimated long-run elasticity is considerably larger than the existing literature, potentially due to methodological differences that allow me to capture additional margins of response. Typical quasi-experimental methods rely on tracking the same consumers before and after a price change, missing investment choices made at the time a home is built or before new tenants move in. In this paper, estimation of long-run elasticities relies on cross-sectional price variation, allowing me to capture additional

margins of response in the comparison of similar households facing different price regimes.

The difference in magnitudes between short- and long-run elasticities suggest that the adoption of durable goods plays an important role in household electricity consumption. I directly observe adoption behaviors of two durable goods that might be used in response to price changes – rooftop solar and utility energy efficiency programs. Consumers are largely unresponsive to prices in their adoption of solar or energy efficiency programs. To further explore the mechanisms driving the high magnitude of long-run price responsiveness that I observe, I estimate how customers across different price regimes respond to temperature. I find that households in the high price region are significantly less responsive to high summer temperatures and low winter temperatures than those in the low price region. Furthermore, the gap between high- and low-price customers becomes more pronounced the longer customers have lived in their current households. While I do not directly observe adoption of other durable goods, these results are consistent with electricity prices having a substantial impact on investment decisions on space cooling.

In addition, I explore the impact that income has on price responsiveness. I find that low-income consumers are less responsive to price changes in the short run, but that low-income consumers are more responsive than higher-income consumers in the long run. These findings highlight that higher income consumers may have more margins to adjust their usage in the short- and medium-run (e.g. more appliances that they are able to turn off in response to price changes), but that prices may play a larger role for low-income household in making investment choices surrounding energy-intensive goods.

The results presented here have important policy implications. Not only are long-run elasticities vital for forecasting electricity demand for a number of applications and stakeholders, but these results have additional importance for climate change and price-based policies. In contrast to past research, I find that electricity consumption is highly responsive to prices in the long run,

demonstrating that electricity prices can provide strong incentives for consumers to undertake emissions-saving behaviors. This highlights the role that price-based policies, such as carbon taxes, can play in decarbonization efforts. When consumers respond to prices by adopting consumption-reducing durable goods and thereby reducing their emissions, price-based policies are an appealing option to internalize emissions externalities. It also, however, emphasizes the important of getting prices right. Electricity prices above the social marginal cost may drive too much adoption in technologies like air conditioning and too little adoption in technologies like electric heat or electric vehicles, potentially leading to losses in social welfare.

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A Appendix

A.1 RD graphs and tables

In the main body text, I show a mix of graphs and tables for each regression discontinuity specification. In this section of the Appendix, tables are shown for specifications where graphs were shown in the main body, and vice versa.

A.2 Robustness checks

A.2.1 Alternative specification with varying bandwidths

To ensure that these results are not driven by specific choices over bandwidth sizes, I test alternative bandwidths of double and half of the size in the preferred specification. Results are shown below for the first stage and reduced form specifications at bandwidths of 0.5 miles and 2 miles respectively. For the IV elasticity estimation, results at 0.5 miles and 2 miles are showed in the main body text in Table 5

Table 11: Cooling Degree Days RD

	CDD
Hi Price	-0.052
	(0.15)
Distance to border	-0.00016
	(0.000093)
Hi x Distance	0.00011
	(0.000097)
Observations	7419339

*Note: Fixed effects include CBG and electric heat. Standard errors are clustered by baseline territory. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

Table 12: Heating Degree Days RD

	HDD
Hi Price	0.13
	(0.21)
Distance to border	0.00041
	(0.00023)
Hi x Distance	-0.00033
	(0.00027)
Observations	7419339

*Note: Fixed effects include CBG and electric heat. Standard errors are clustered by baseline territory. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

Figure 17: Solar adoption

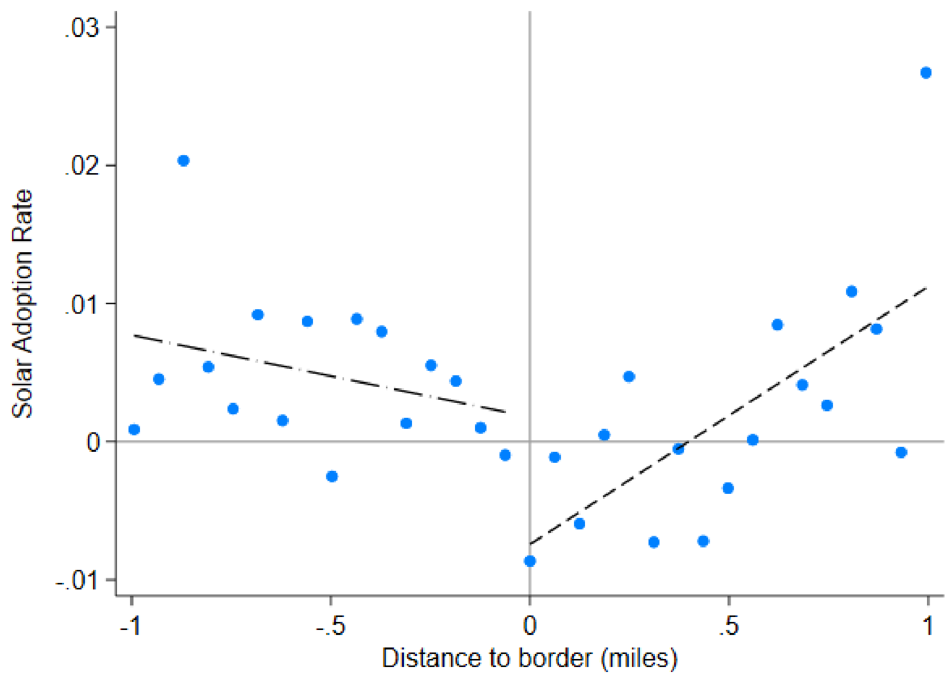


Figure 18: Energy efficiency adoption

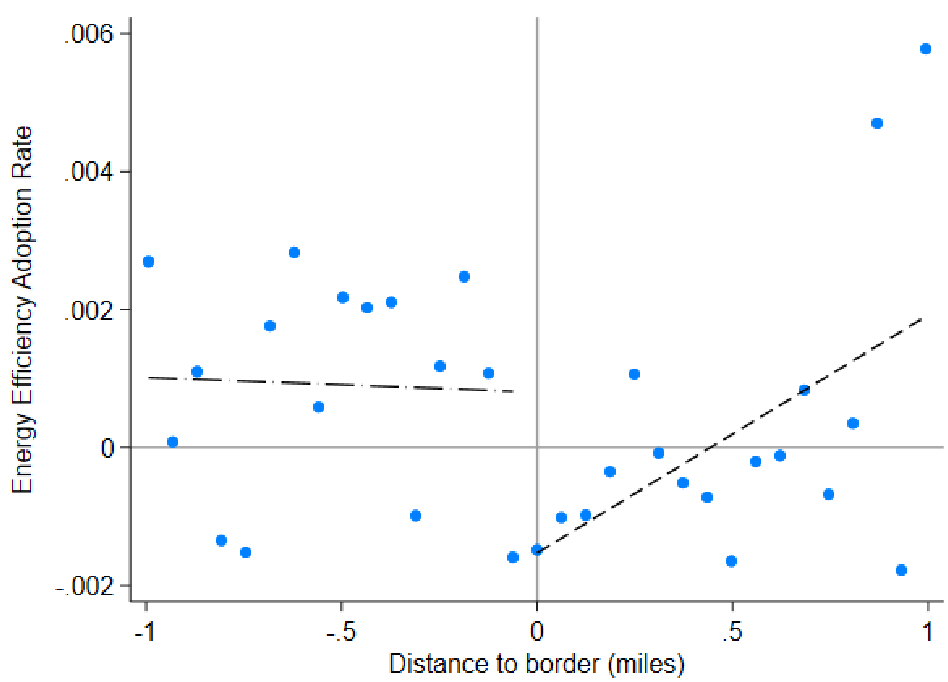


Figure 19: Consumption RD by Income

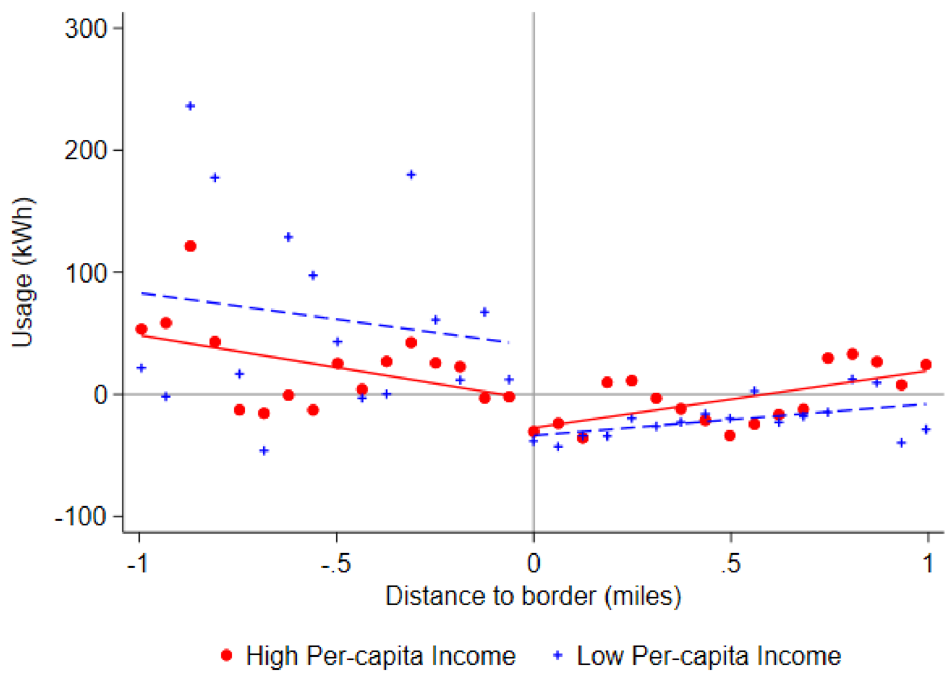


Figure 20: First stage RD - baseline (Bandwidth = 0.5 miles)

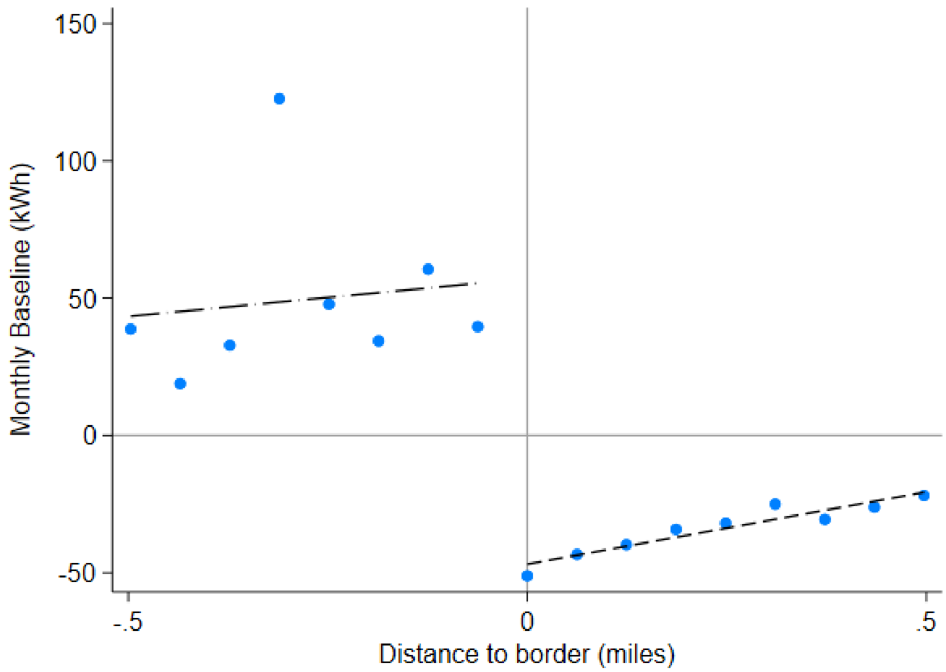


Figure 21: First stage RD - average variable price (Bandwidth = 0.5 miles)

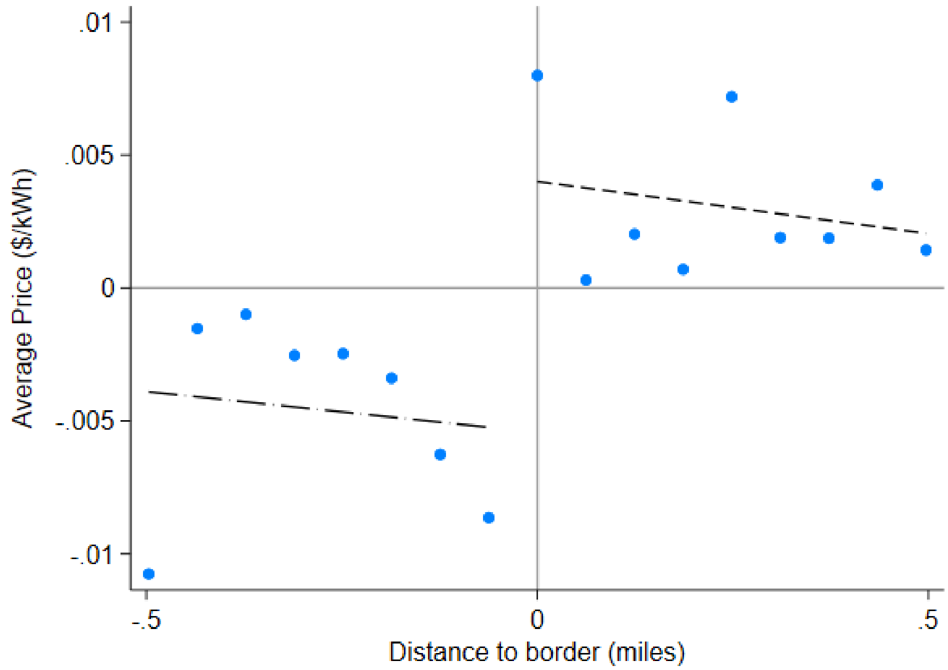


Figure 22: Reduced form RD (Bandwidth = 0.5 miles)

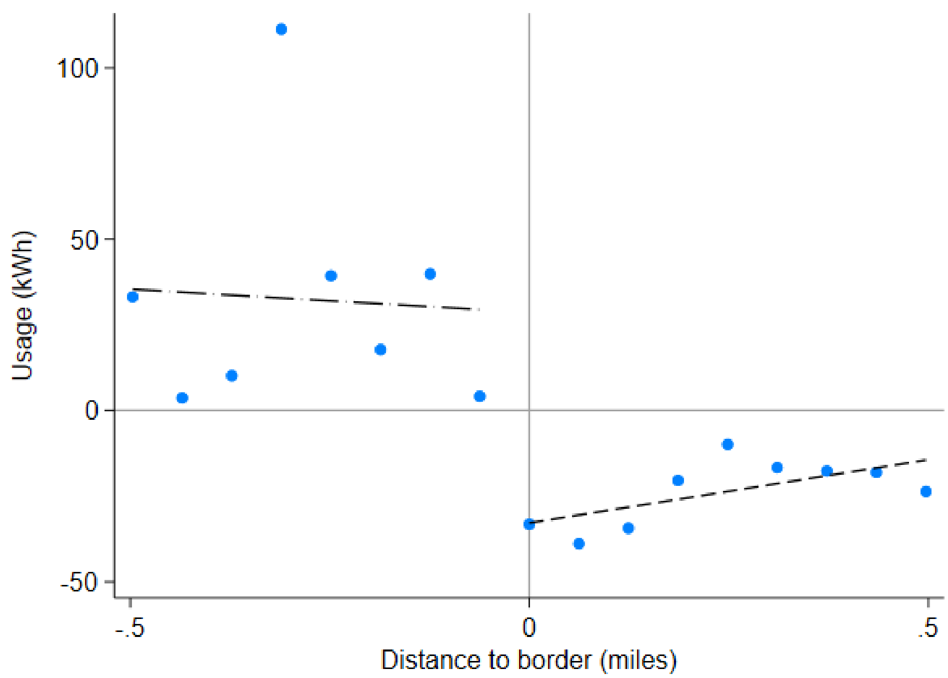


Figure 23: First stage RD - baseline (Bandwidth = 2 miles)

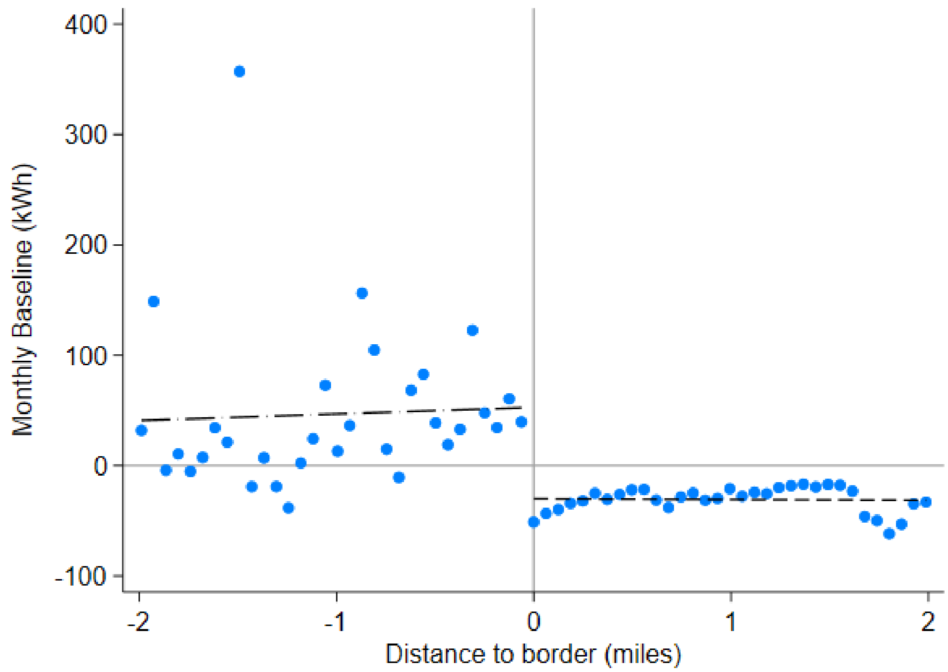


Figure 24: First stage RD - average variable price (Bandwidth = 2 miles)

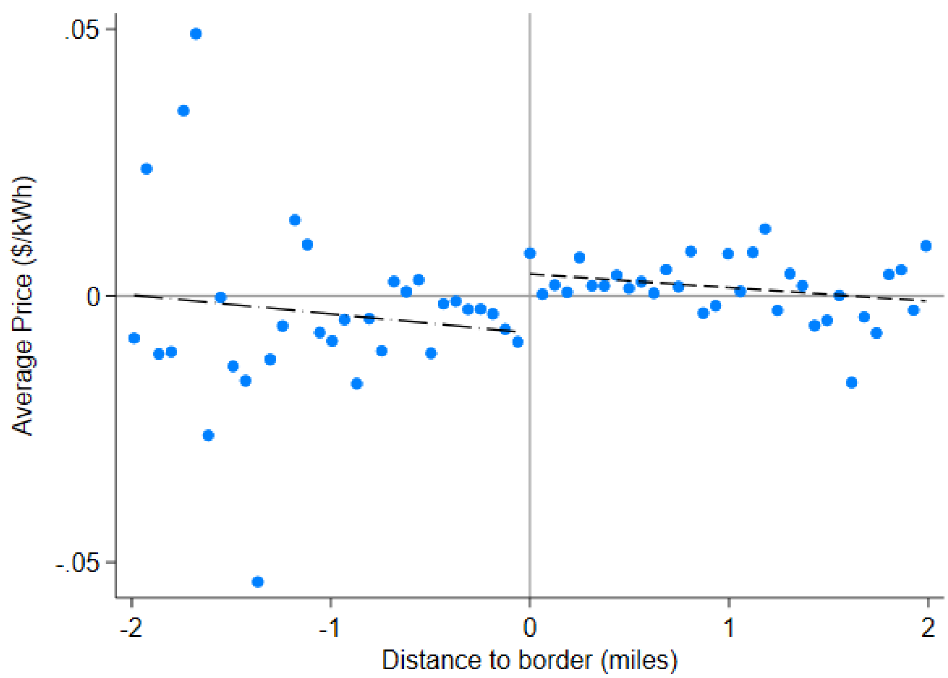
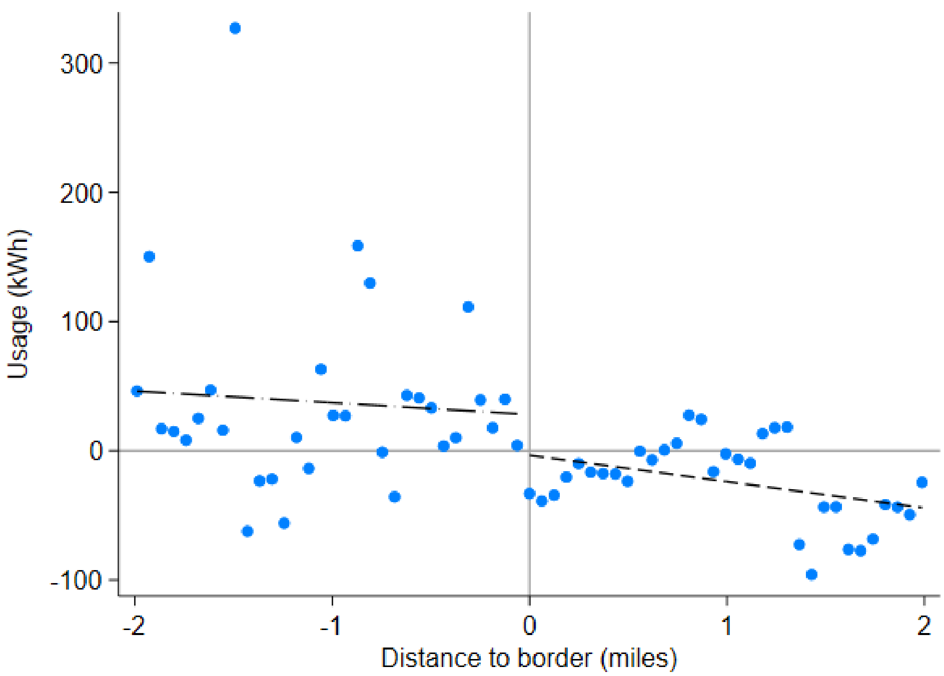


Figure 25: Reduced form RD (Bandwidth = 2 miles)



A.2.2 Alternative parametric assumptions

Here, I estimate regression discontinuity specifications under different parametric assumptions. In particular, while the preferred specification uses local linear regressions on either side of the baseline discontinuity, I show that alternative specifications that assume flat functional forms on either side of the discontinuity do not meaningfully change the magnitude or direction of my main results. I show alternative specifications for the first stage and reduced form regression discontinuities.

Figure 26: First stage RD - baseline (Flat parametric assumptions)

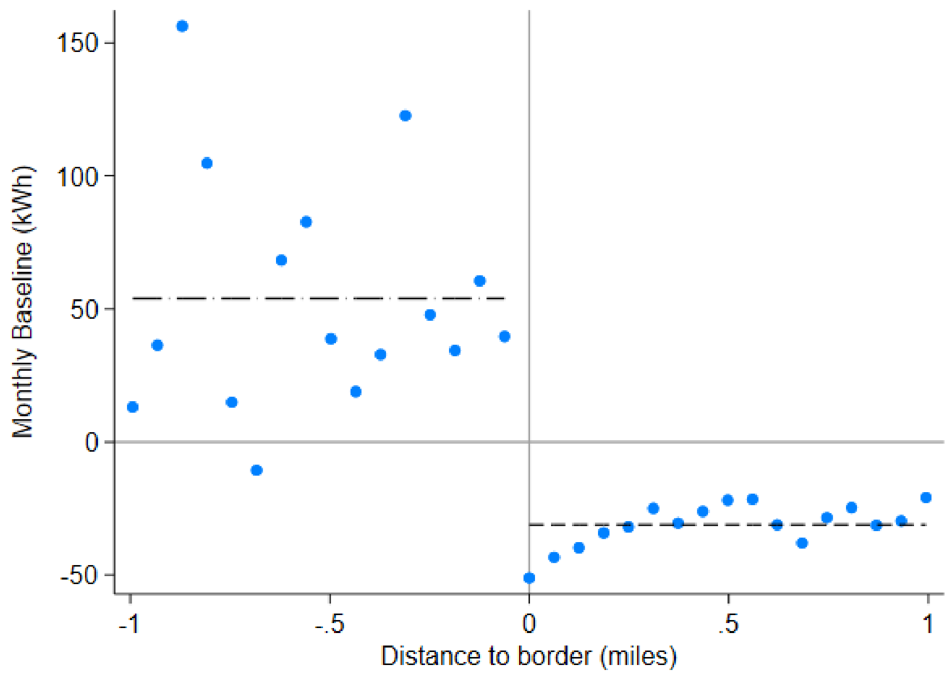


Figure 27: First stage RD - average variable price (Flat parametric assumptions)

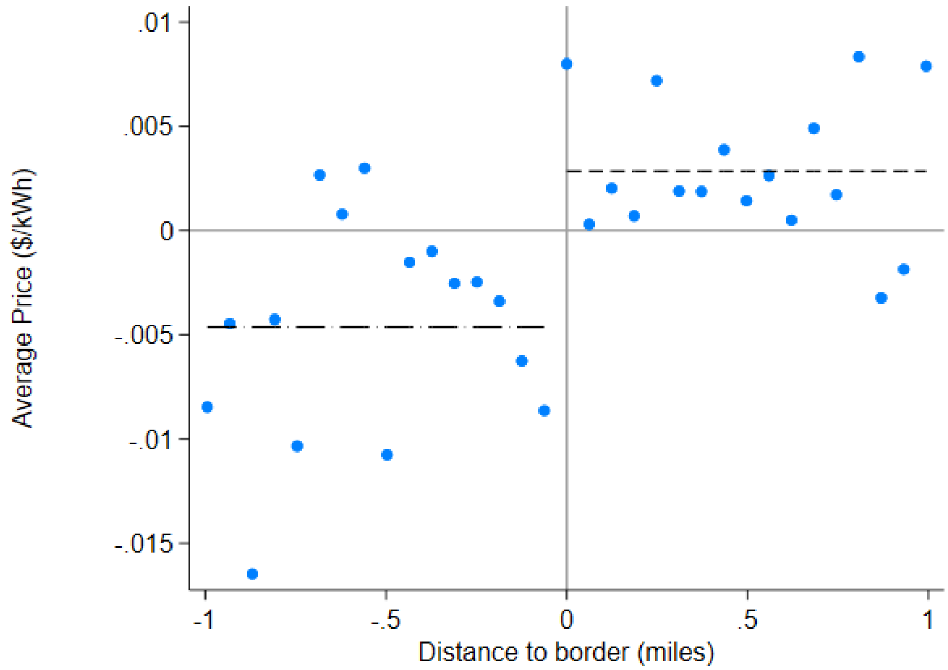
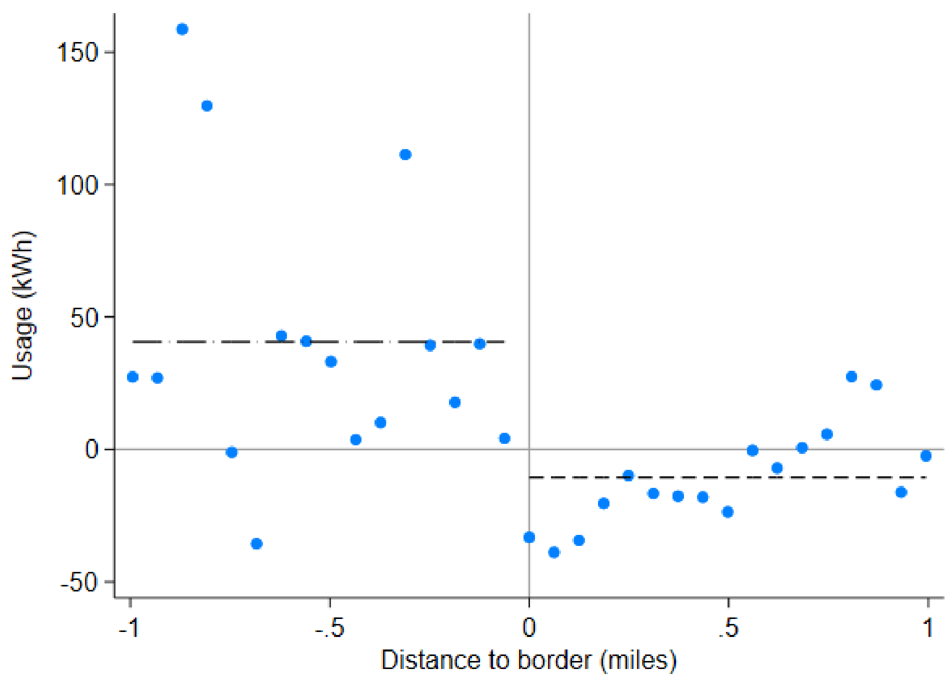


Figure 28: Reduced form RD (Flat parametric assumptions)



A.2.3 Alternative price definitions

Here, I explore how long-run elasticity estimates vary under different definitions of price. There are two concerns that I check here: first, the endogeneity of prices later in the sample given that consumption may change as a result of durable goods investment; and second, first stage estimates that are biased downward due to attenuation in the differences in the price schedule over time. I use alternative price definitions to test both concerns.

Potential endogeneity of prices

In the main body specifications, one might be concerned about endogeneity, where the adoption of an energy-saving technology might cause a dramatic change in usage and push a household into a lower pricing tier. I test this concern with two alternative definitions of price: first, I calculate what monthly average variable price would have been under monthly consumption levels from 2008 (the first year of data in my sample) and under the present-period price schedule[22]. Second, to confirm that prices aren't dependent on that single year of data, I repeat the same exercise with 2009 consumption levels. As shown in Tables 13 and 16, I find similar estimates, demonstrating that this potential endogeneity is not driving the observed results.

Table 13: Price under 2008 consumption

	1 mile
Log Average Price under 2008 Consumption	-1.99***
	(0.48)
Distance to border	-0.00012***
	(0.000035)
Hi x Distance	0.00025***
	(0.000048)
Observations	7270569
F	68.8

*Note: Fixed effects include CBG-by-month and a binary variable indicating electric heat. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

[22]Specifically, I match according to the month. For instance, average variable price in February 2011 would be determined from consumption levels in February 2008 and the price schedule in February 2011.

Table 14: Price under 2009 consumption

	1 mile
Log Average Price under 2009 Consumption	-2.01***
	(0.47)
Distance to border	-0.00012***
	(0.000035)
Hi x Distance	0.00025***
	(0.000048)
Observations	7276524
F	61.8

*Note: Fixed effects include CBG-by-month and a binary variable indicating electric heat. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

Potential bias due to flattening of the rate schedule

In Figure 4, it's clear that there is a flattening in rates over time. In fact, PG&E went from five tiers to two over the course of the sample. This flattening could attenuate differences in prices across the border, since cross-sectional price differences in this setting is driven by the jumps in the price schedule. If households respond to large differences in price early in the sample by investing in energy-saving durable goods, but those price differences attenuate over time, then the first stage estimates in the IV elasticity specification (Equations 5 and 6) could be biased downwards, thereby inflating the estimated long-run elasticity. To test for this, I re-run my first stage and IV estimation under an alternative definition of price: I define price according to the 2008 price schedule[23]. Hence, for a 2020 bill, I calculate what their average variable prices would have been at their 2020 level of consumption and using their 2020 baseline, but under the 2008 price schedule.

Under this alternative price definition, if the flattening of the price schedule is biasing the observed first stage results and elasticity, I would expect to see first stage estimates that are substantially higher than in the main specification. This would result in an elasticity estimate that is substantially lower. However, as shown in Tables 15 and 16, I find very few differences between these specifications and those in the main body text in either the first stage or IV specification. This suggests that the flattening of rates is not causing meaningful bias in the specifications in the main text.

[23]For customers on the standard rate, the rate schedule is fixed to 2008. For customers later in the sample on time-of-use rates hat were introduced after 2008, I fix those price schedules to their levels at the time that the rate was introduced.

Table 15: First stage under 2008 price schedule

	1 mile
hi	0.015***
	(0.0014)
Distance to border	-0.0000027**
	(0.0000010)
Hi x Distance	0.0000077***
	(0.0000017)
Observations	7051197

*Note: Fixed effects include CBG-by-month and electric heat-by-season. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

Table 16: IV under 2008 price schedule

	1 mile
Log Average Price under 2008 Price Schedule	-2.18***
	(0.61)
Distance to border	-0.00014***
	(0.000033)
Hi x Distance	0.00029***
	(0.000057)
Observations	7014818
F	92.7

*Note: Fixed effects include CBG-by-month and electric heat-by-season. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

A.3 Definition of baseline territories

Pacific Gas and Electric Company
U 39 San Francisco, California

	Revised	*Cal. P.U.C. Sheet No.*	34601-E
Cancelling	Revised	*Cal. P.U.C. Sheet No.*	12081-E

ELECTRIC PRELIMINARY STATEMENT PART A Sheet 1
DESCRIPTION OF SERVICE AREA & GENERAL REQUIREMENTS

A. DESCRIPTION OF SERVICE AREA AND GENERAL REQUIREMENTS

1. TERRITORY SERVED BY PG&E

a. The Pacific Gas and Electric Company (PG&E) supplies electric service in all or portions of 47 counties in the northern and central part of the State of California. A map of counties and associated zip codes that PG&E provides service to can be found on PG&E's website at http://www.pge.com/tariffs/ under electric maps. (N) I (N)

b. The baseline territories used in the residential rate schedules are shown below for each county. Baseline territories correspond with elevation lines, unless specific boundaries were drawn to avoid dividing communities or neighborhoods as described in Section A.1.c. (T) (T)

County	Locations, Elevation Range or Description at c. Below	Baseline Territory Code
ALAMEDA	c.(1)(S)	S
	c.(1)(T)	T
	All Other	X
ALPINE*	All	Z
AMADOR	Under 1,500'	S
	1,500'-3,000'	P
	3,001'-6,000'	Y
	Over 6,000'	Z
BUTTE	Under 1,500'	S
	1,500'-3,000'	P
	3,001'-4,800'	Y
	Over 4,800'	Z
CALAVERAS	Under 1,500'	S
	1,500'-3,000'	P
	3,001'-6,000'	Y
	Over 6,000'	Z
COLUSA	All	S
CONTRA COSTA	c.(2)(S)	S
	c.(2)(T)	T
	All Other	X
EL DORADO*	Under 1,500'	S
	1,500'-3,000'	P
	3,001'-6,000'	Y
	Over 6,000'	Z
FRESNO*	Under 3,500'	R
	3,501'-6,500'	Y
	Over 6,500'	Z
GLENN	Under 3,000'	S
	Over 3,000'	Y
HUMBOLDT	c.(3)(V)	V
	All Other	Y
KERN*	Under 1,000'	W
	Over 1,000'	R
KINGS*	All	W
LAKE*	All	P
LASSEN*	Under 4,800'	Y
	Over 4,800'	Z

*Pertains to PG&E electric service area only.

(Continued)

Advice	4535-E-A	*Issued by*	*Date Filed*	December 15, 2014
Decision		***Steven Malnight***	*Effective*	December 17, 2014
		Senior Vice President	*Resolution*	
		Regulatory Affairs		

A. DESCRIPTION OF SERVICE AREA AND GENERAL REQUIREMENTS (Cont'd.)

1. TERRITORY SERVED BY PG&E (Cont'd.)

County	Locations, Elevation Range or Description at c. Below	Baseline Territory Code	
MADERA*	Under 4,000'	R	
	4,001'-6,500'	Y	
	Over 6,500'	Z	
MARIN	c.(4)(T)	T	
	All Other	X	
MARIPOSA	Under 3,500'	R	
	3,501'-6,000'	Y	
	Over 6,000'	Z	
MENDOCINO	c.(5)(T)	T	
	All Other	X	
MERCED	All	R	
MONTEREY	c.(6)(T)	T	
	All Other	X	
NAPA	All	X	
NEVADA	Under 1,500'	S	
	1,500'-3,000'	P	
	3,001'-5,500'	Y	
	Over 5,500'	Z	
PLACER*	Under 1,500'	S	
	1,500'-3,000'	P	
	3,001'-5,500'	Y	
	Over 5,500'	Z	
PLUMAS*	Under 4,800'	Y	
	Over 4,800'	Z	
SACRAMENTO	All	S	
SAN BENITO	c.(7)(T)	T	
	All Other	X	
SAN FRANCISCO	All	T	
SAN JOAQUIN	All	S	
SAN LUIS OBISPO	c.(8)(R)	R	
	c.(8)(T)	T	
	All Other	X	
SAN MATEO	c.(9)(T)	T	
	c.(9)(Q)	Q	
	All Other	X	
SANTA BARBARA*	c.(10)(R)	R	
	c.(10)(T)	T	
	All Other	X	
SANTA CLARA	c.(11)(Q)	Q	
	All Other	X	
SANTA CRUZ	Under 1,500'	T	
	1,500' & Over	Q**	(T)

* Pertains to PG&E electric service area only.
** Territory Q also includes customers in the following locations (zip codes) within Santa Cruz County at elevations less than 1,500 feet: Ben Lomond (95005), Boulder Creek (95006), Brookdale (95007), Felton (95018), Mount Hermon (95041) and unincorporated areas (95033). (N)

(Continued)

ELECTRIC PRELIMINARY STATEMENT PART A Sheet 3
DESCRIPTION OF SERVICE AREA & GENERAL REQUIREMENTS

A. DESCRIPTION OF SERVICE AREA AND GENERAL REQUIREMENTS (Cont'd.) (T)

1. TERRITORY SERVED BY PG&E (Cont'd.) (T)

County	Locations, Elevation Range or Description at c. Below	Baseline Territory Code	
SHASTA	Under 2,000'	R	(L)
	2,001'-4,500'	Y	
	Over 4,500'	Z	
SIERRA	Under 5,500'	Y	
	Over 5,500'	Z	
SISKIYOU*	Under 4,500'	Y	
	Over 4,500'	Z	
SOLANO	c.(12)(X)	X	
	All Other	S	
SONOMA	c.(13)(T)	T	
	All Other	X	
STANISLAUS	All	S	
SUTTER	All	S	
TEHAMA	Under 2,500'	R	
	2,501'-4,800'	Y	
	Over 4,800'	Z	
TRINITY	Under 2,000'	X	
	2,001'-4,500'	Y	
	Over 4,500'	Z	
TULARE*	Under 1,000'	W	
	1,001'-3,500'	R	
	3,501'-6,500'	Y	
	Over 6,500'	Z	
TUOLUMNE*	Under 1,500'	S	
	1,500'-3,500'	P	
	3,501'-6,000'	Y	
	Over 6,000'	Z	
YOLO	All	S	
YUBA	Under 1,500'	S	
	1,500' & Over	P	(L)

* Pertains to PG&E electric service area only. (D)

(Continued)

A.4 Marginal price regressions

This section of the Appendix shows marginal price elasticity estimates (in contrast with the average variable price elasticity estimates shown in the main body of this paper). While short-run marginal price elasticity estimates are shown in the main body, this Appendix section shows long-run marginal price elasticity estimates.

Table 17: Long-run marginal price first stage

	1 mile	1/2 mile	2 miles
hi	0.032***	0.029***	0.035***
	(0.0024)	(0.0021)	(0.0028)
Distance to border	-0.0000058**	-0.0000030	-0.00000086
	(0.0000025)	(0.0000022)	(0.0000014)
Hi x Distance	0.000017***	0.000021***	0.00000061
	(0.0000040)	(0.0000036)	(0.0000026)
Observations	7463542	5694337	9107026

*Note: Fixed effects include CBG-by-month. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

Table 18: Long-run IV estimate of marginal price elasticity

	1 mile	1/2 mile	2 miles
Log Marginal Price	-1.50***	-1.59***	-1.30**
	(0.44)	(0.44)	(0.43)
Distance to border	-0.00014***	-0.00015***	-0.000036
	(0.000039)	(0.000022)	(0.000024)
Hi x Distance	0.00029***	0.00039***	0.000014
	(0.000060)	(0.000088)	(0.000038)
Observations	7327914	5599033	8932262
F	108.3	107.3	115.1

*Note: Fixed effects include CBG-by-month. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

A.5 Heterogeneity by CBG-level characteristics

This section of the Appendix shows heterogeneity estimates. Across all CBG-level demographic traits, I estimate short- and long-run elasticities for two separate groups – those above and below the median CBG. Below, I show estimates for per-capita income, home ownership, age of housing stock, race, and within-CBG income inequality (as measured by a Gini coefficient).

Figure 29: Long-run estimates by CBG-level per-capita income

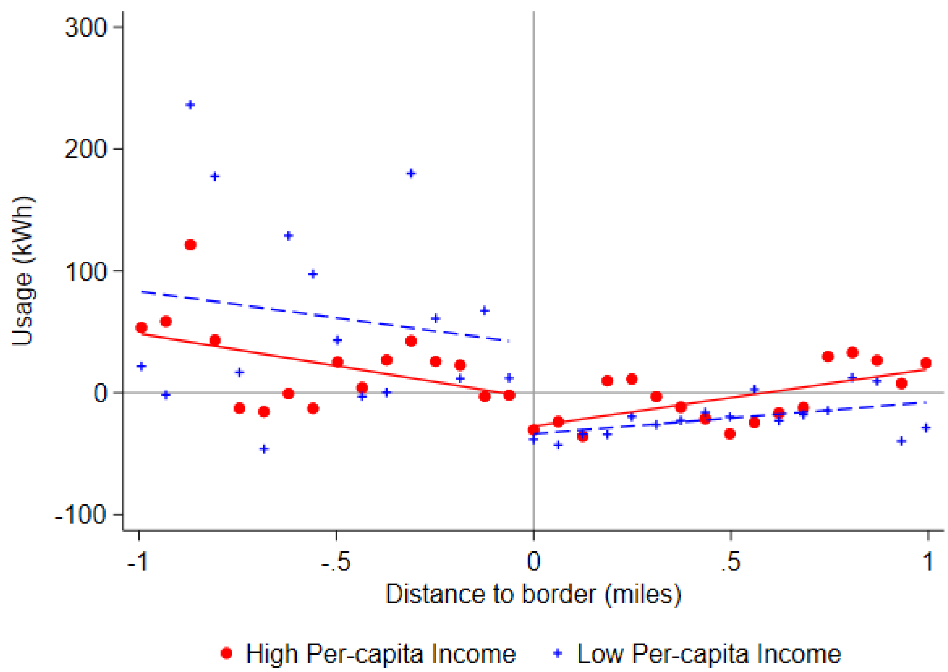


Figure 30: Long-run estimates by CBG-level home ownership rate

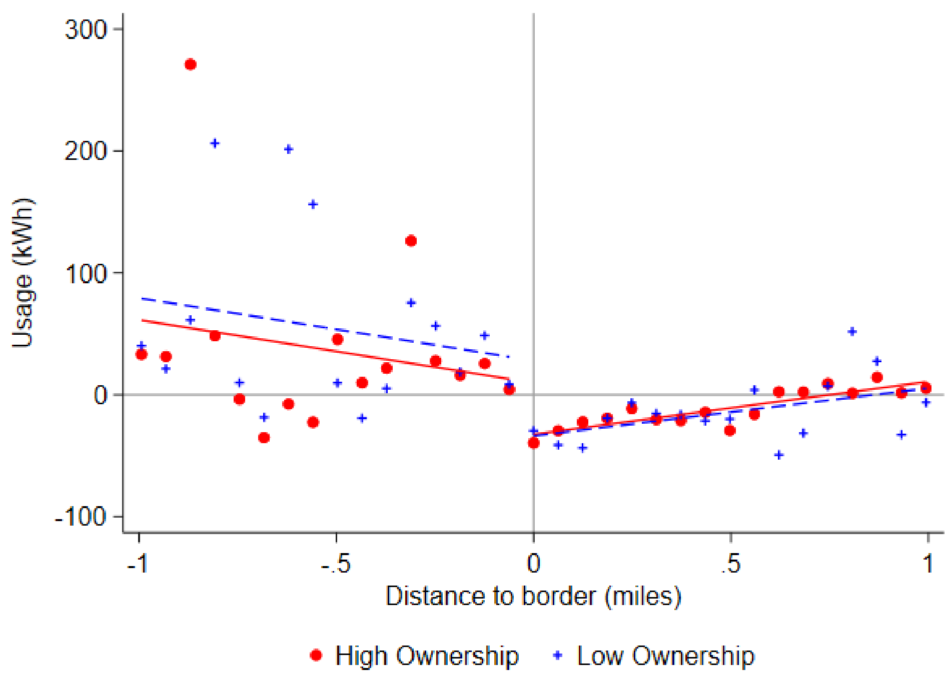


Figure 31: Long-run estimates by CBG-level age of housing stock

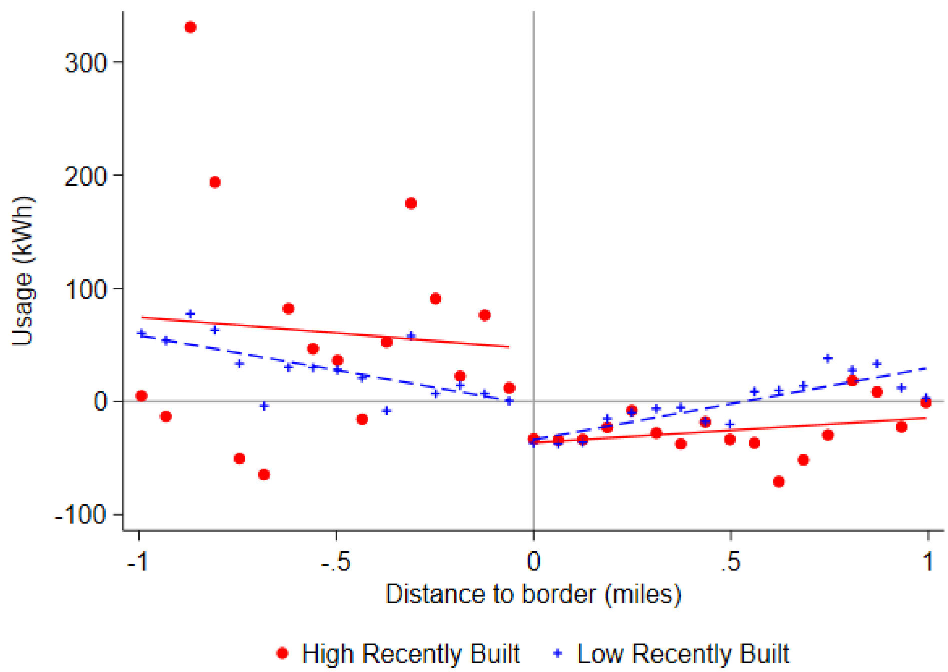


Figure 32: Long-run estimates by CBG-level race

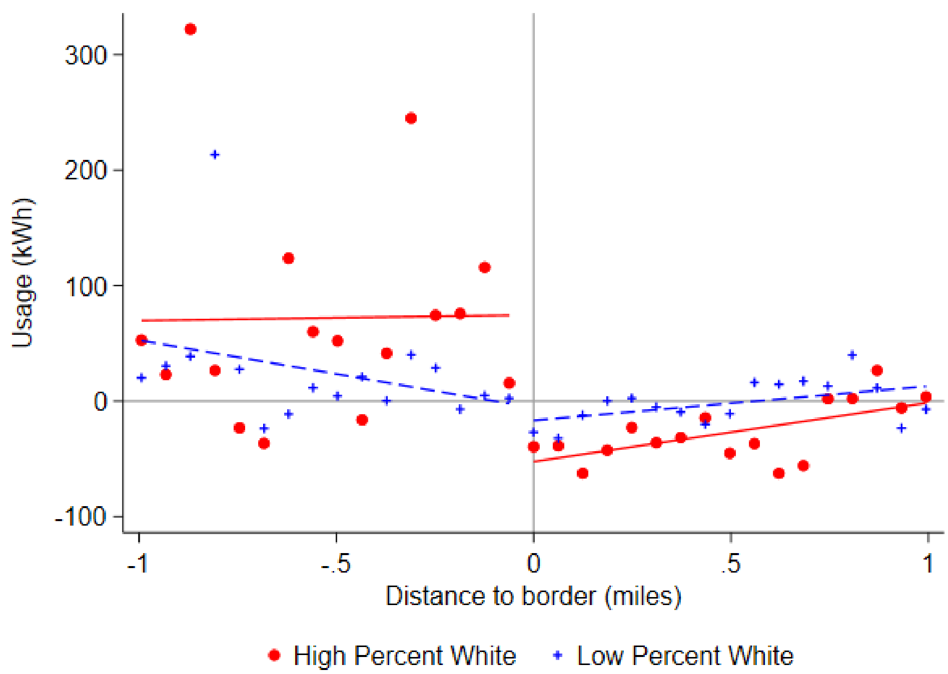
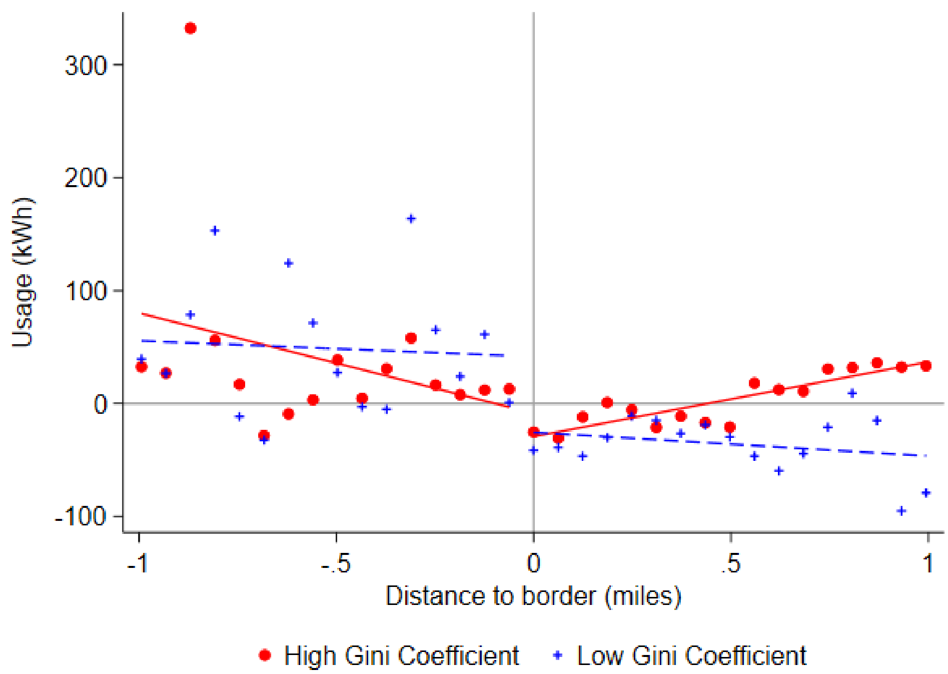


Figure 33: Long-run estimates by CBG-level Gini coefficient



A.6 Supplementary heterogeneity results

Table 19: Elasticity estimation by income

	Low income	High income
Log Average Price	-3.34***	-1.02**
	(0.59)	(0.39)
Distance to border	-0.000047	-0.00019***
	(0.000046)	(0.000015)
Hi x Distance	0.00019***	0.00031***
	(0.000055)	(0.000048)
Observations	4080008	3247906
F	34.7	59.6

*Note: This table shows two separate instrumental variable regressions by income of log consumption on price, instrumenting for price with distance to the baseline territory boundary. Income is proxied with CBG-level per-capita income. Fixed effects include CBG-by-month and a binary variable indicating electric heat. Standard errors are clustered by baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

A.7 Medium-run responses to prices

Here, I build on the short-run specifications to estimate elasticities in the medium run. In my primary medium-run specification, I refer to the medium run as a time horizon of four years. Currently, there is little existing work in the literature on medium-run elasticities, especially in a quasi-experimental setting. Deryugina, MacKay and Reif (2019) find that customers are more responsive in the medium-run than in the short-run. This is is consistent with a number of studies using aggregated state-level data that similarly find that consumption responses to price build over time. In this section, I estimate how four-year consumption differences can be attributed to price changes that occur within that four-year period.

There are several different channels through which customers might respond to prices. After observing a change in price, consumers might respond in the short run by reducing their consumption of certain appliances – for example, a consumer might turn off their lights more frequently. If this short-run behavior becomes a habit for the consumer, we might continue to see this response carry through to the medium-run. However, customers may also respond by changing their investment of durable goods, such as energy efficient appliances, electric heat, or solar panels. We should expect that durable good adoption will impact consumption in both the short-run and the medium-run. These two channels – habit formation of conservation behaviors and durable good adoption – are the primary channels through which past prices can impact current consumption.

In order to estimate medium-run elasticities in this setting, I extend Ito's approach using time lags. Now, the dependent variable is the difference in consumption between the contemporaneous period and four years prior for a given household. I include the full price path as right-hand side variables, with a series of annual price differences within a four-year window as the primary covariates of interest. I used two-stage least squares, with four endogenous variables and four

instruments:

$$\text{First stage: } \Delta\ln(MP_{i,t,l}) = \ln(MP_{i,t-12l}) - \ln(MP_{i,t-12(l+1)}) \text{ for each } l \in 0,1,2,3 \tag{9}$$

$$\text{Second stage: } \Delta\ln(c_{i,t,t-48}) = \sum_{l=0}^{3} \beta_l \, \Delta\ln(\widehat{MP}_{i,t,l}) + f_t(c_{i,t-60}) + \gamma_{ct} + \eta_{it} \tag{10}$$

where $\Delta\ln(c_{i,t,t-48}) = \ln(c_{i,t}) - \ln(c_{i,t-48})$ and $f_t(c_{i,t-60})$ is a set of dummy variables determined by the percentile of consumption in period $t - 60$.

As in the short-run specifications, each price difference is endogenous to consumption due to the nature of increasing block pricing. Again, I use simulated instruments to solve this issue. For each endogenous price covariate, an associated simulated instrument is included.

In the short-run specifications, consumption levels from period $t - 6$ were used in the instrument. Here, however, consumption in period $t - 6$ is endogenous to the price differences included as covariates. Instead, in the medium-run specifications, consumption levels from period $t - 60$ (one year prior to the first included price period) are used. This ensures that the instrument isolates exogenous changes in the price schedule and eliminates all endogenous price variation driven by consumption changes. Note that this specification includes only utility accounts continuously present in the sample over the course of five years (months ranging from t to $t-60$). Any customers who move over the course of this period are dropped from the sample. Hence, the external validity of these medium-run estimates is limited to consumers who are fairly stable and live in a single location for an extended period of time.

It's important to note that the empirical setting in this paper is quite different than in past work, including Deryugina, MacKay and Reif (2019). Deryugina et al. leveraged on a one-time change in prices and followed customers' demand levels over time. Here, price schedule fluctuations frequently occur and impact customers differently depending on their baseline territories and underlying consumption levels. As such, the interpretation of estimates is different in this setting: while elasticity estimates in Deryugina et al. should be interpreted as a consumption response to a single permanent change in price, the estimates in this paper tell us how to attribute changes in consumption to changes in price over the relevant period. When consumption changes over a four year period, how much of that change should be attributed to price changes in each year? Examination of each coefficient in the regression demonstrates how elasticities evolve over time.

Results of these medium-run regressions over a four-year period are shown in Table 20. These results demonstrate that responses to prices last over the course of several years, indicating that habits and/or durable good adoption play a vital role. When including past price periods, customers are similarly responsive to short-run fluctuations in price, with a price elasticity of -0.18. This elasticity stays close to -0.2 through two years, before fading towards -0.1 by the fourth year.

In the Table 21, I also estimate medium-run elasticities over an eight-year period. Note that this sample is even more highly selected to include only customers who do not move over a nine year period within my twelve year sample. Again, the external validity of these estimates is restricted only to consumers who live in a single location for an extended period of time – in this case, nine years.

These results are consistent with a combination of a short-run transient behavioral responses and significant durable good investment. After price fluctuations, consumers respond by changing their consumption. However, customers may also respond to price changes by investing in durable goods, which last for the duration of the sample. As a result, they still demonstrate responsiveness to price changes that occurred in more distant periods – in this case, three to four years prior to the contemporaneous period.

Table 20: Dynamic medium-run average variable price elasticities

	kWh (1)
$\Delta\ln(AP\_it)$	-0.18***
	(0.044)
$\Delta\ln(AP\_i,t,1)$	-0.19***
	(0.042)
$\Delta\ln(AP\_i,t,2)$	-0.13***
	(0.030)
$\Delta\ln(AP\_i,t,3)$	-0.12***
	(0.034)
Observations	2606624
F	194.9

*Note: Fixed effects include CBG-by-month and consumption deciles from the period twelve months prior to the initial price period. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

In addition, I estimate heterogeneity in medium-run elasticities across income, again using CARE enrollment as a proxy for income, as shown in Table 22. Consistent with the short-run results, non-CARE (higher-income) consumers are more responsive to changes in their electricity prices in all periods.Once again, this suggests that investment in durable goods may play a substantial role in how consumers respond to energy prices.

Furthermore, these results suggest that consumers' responses to price changes may accumulate over time as consumers continue to respond to prices from four years prior. However, the type of dynamic two-way fixed effects panel regressions shown to this point only allow for evaluation up to the length of the observed sample, and may miss important mechanisms, such as durable goods investments in new homes. These are better captured by long-run elasticities, as described in Section 4.1.

Table 21: Dynamic medium-run price elasticities - all average variable prices (8 year stable sample)

	12 (1)
$\Delta\ln(AP\_it)$	-0.072
	(0.059)
$\Delta\ln(AP\_i,t,1)$	-0.14**
	(0.058)
$\Delta\ln(AP\_i,t,2)$	-0.030
	(0.053)
$\Delta\ln(AP\_i,t,3)$	0.048
	(0.056)
$\Delta\ln(AP\_i,t,4)$	0.027
	(0.068)
$\Delta\ln(AP\_i,t,5)$	-0.0088
	(0.056)
$\Delta\ln(AP\_i,t,6)$	-0.058
	(0.061)
$\Delta\ln(AP\_i,t,7)$	-0.21**
	(0.088)
Observations	955837
F	62.6

*Note: Fixed effects include CBG-by-month and consumption deciles from the period twelve months prior to the initial price period. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*

Table 22: Dynamic medium-run average variable price elasticities by CARE

	CARE (1)	nonCARE (2)
$\Delta\ln(AP\_it)$	-0.11**	-0.21***
	(0.053)	(0.050)
$\Delta\ln(AP\_i,t,1)$	-0.12**	-0.23***
	(0.052)	(0.049)
$\Delta\ln(AP\_i,t,2)$	0.0038	-0.18***
	(0.043)	(0.034)
$\Delta\ln(AP\_i,t,3)$	-0.056	-0.13***
	(0.052)	(0.037)
Observations	413612	2192841
F	166.4	200.7

*Note: Fixed effects include CBG-by-month and consumption deciles from the period halfway between the present period and the lagged consumption period. Standard errors are clustered by CBG-baseline territory and by month of sample. ***, **, * indicate significance at the 1% and 5% and 10% level, respectively.*